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**Who Cares When You Close Down?
The Effects of Primary Care Practice Closures
on Patients**

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Who Cares When You Close Down? The Effects of Primary Care Practice Closures on Patients

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Abstract

This paper investigates the consequences that patients face when their regular primary care provider closes down her practice, typically due to retirement. We estimate the causal impact of closures on patients' utilization patterns, medical expenditures, hospitalizations, and health plan choice. Employing a difference-in-difference framework, we find that patients who experience a discontinuity of care persistently adjust their utilization pattern by shifting visits away from ambulatory primary care providers (-12%) towards specialist care (+10%), and hospital outpatient facilities (+5%). The magnitude of these effects depends considerably on the local availability of primary care. We also observe that patients with chronic conditions shift their utilization more strongly towards other providers. Our results have potential implications for health policy in at least two dimensions: practice closures may lead to an inefficient use of healthcare services and deteriorate access to primary care, particularly in regions where the supply of primary care doctors is low.

Keywords: Continuity of Care; Healthcare Utilization; Healthcare Expenditures; Primary Care; General Practitioners

JEL: D12, I11, I12, I31

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1 INTRODUCTION

Mounting evidence documents that the supply of primary care physicians is positively associated with health outcomes and negatively associated with healthcare costs (Macinko et al., 2003; Starfield et al., 2005; Ricketts and Holmes, 2007; Gravelle et al., 2008; Chang et al., 2011; Shi, 2012). In many countries, the sufficient provision of primary care has become a pressing issue because healthcare systems face an aging physician workforce (OECD, 2017). The looming shortage of general practitioners (GPs) is critically related to the insufficient inflow of primary care residents, who must replace their retiring colleagues (Bodenheimer and Pham, 2010; Huang and Finegold, 2013). Consequently, self-employed GPs may be increasingly forced to close down their private practice when they retire because they cannot find a successor. The important question is to what extent regular patients experience adverse effects when they lose their (potentially long-standing) source of care (Scott, 2000). To date, the existing literature offers no evidence as to how the retirement of GPs and practice closures affect patients.

This paper aims to fill this gap: The objective is to analyze the various causal impacts on patients that arise when their regular GP closes down her practice. In particular, we study how patients adjust their utilization across different types of providers, and we examine the effects on health-related outcomes such as hospitalization rates and healthcare expenditures. We also explore effect heterogeneity to shed light on the question as to which groups of patients are more strongly affected than others.

From the perspective of patients, practice closures generate an *interpersonal discontinuity of care* and lower the *availability* of local primary care services. First, these may lead to inefficient utilization of healthcare services (e.g., non-urgent emergency department visits) and thus has implications for health policy and social health insurance. Second, the retirement of their regular GP may have adverse effects on patients' outcomes, since interpersonal continuity of care is generally found to be beneficial to patients' health (Saultz and Lochner, 2005). Moreover, practice closures may have important heterogeneous effects. For example, the impact in peripheral areas with low physician density may be more pronounced compared to areas with a high physician density.

The empirical strategy of this paper is based on a weighted difference-in-difference framework. We compare average outcomes before and after practice closures between an affected group of patients (the treatment group) and an unaffected group that does not experience any changes in primary care provision (the control group). We exploit the fact that the occurrence of practice closures is largely an exogenous source of variation that is mainly a function of the physician's age and does not depend on changes in patient characteristics. This allows us to identify and estimate causal effects under very plausible assumptions.

We study the effects of practice closures that occurred in Switzerland from 2006 to 2015. The empirical analysis combines two data sources. First, we use detailed claims data from a major Swiss health insurer that provides mandatory health insurance to about 1.2 million individuals annually. This data is used to construct a matched patient-provider panel dataset. Second, we collect data on closures of primary care practices by complementing information from administrative data with extensive field research.

The main results are briefly summarized as follows. First, we find robust evidence that patients respond to the closure of their regular primary care provider by changing their utilization patterns. The quarterly number of GP visits falls by 17 visits per 100 persons (-12%). In contrast, practice closures cause an increase in visits to specialist practices (+7 visits or +10%) and hospital outpatient facilities (+2 visits or +5%). Overall, the total number of visits decreases by 8 per 100 persons each quarter (-3%). Second, the results show that while the interruption of primary care provision has no significant impact on total healthcare expenditures (HCE), the costs per visit increase by roughly 5%. Overall, these results indicate that disruptions in primary care provision may entail a more inefficient use of healthcare services as patients shift their utilization towards less cost-efficient sources. In contrast to some existing studies, we do not find any significant impact on the hospitalization rate, which suggests that the true effect size is probably small. Finally, we also document effects on health plan choice: some affected patients switch from a preferred provider organization (PPO) to a health maintenance organization (HMO).

Importantly, we also find interesting evidence on heterogeneous effects. First, a practice closure in a region with low availability of primary care reduces the *total* number of visits by 6%, while there is no significant effect in regions with high availability. These effects differ because substitution towards other sources of care is much easier in high-availability areas, where patients have better access to alternative providers such as walk-in clinics or emergency departments of hospitals. Second, we document differences between patients with and without chronic conditions. Patients with chronic conditions shift their visits more strongly towards specialist care and hospital outpatient care. The same holds true if the sample is restricted to patients with ambulatory-care sensitive conditions (ACSCs) and those with diabetes or hypertension. Third, we find only small differences with regard to gender, age groups (above and below 65), and health plan choice. In our view, these results bear implications for healthcare planning: Appropriate measures may contribute in attenuating the effects, for example, by assisting patients when they have to transfer to a new primary care provider or by creating incentives for providers to settle in low-availability areas.

While there is, to our knowledge, no literature on the effects of practice closures on patients, our findings contribute to two related strands of literature. First, a series of studies document negative effects of *hospital* closures on health outcomes of local residents, with the magnitude depending on the distance to the next hospital (see, e.g., Buchmueller et al., 2006; Avdic, 2016). We add further evidence from a related setting. Second, our findings add valuable causal evidence to the literature that deals with the role of *continuity of care* in primary care (see, e.g., Saultz and Lochner, 2005; van Walraven et al., 2010). These studies mostly report a positive association between interpersonal continuity and health outcomes, but the evidence is mostly descriptive.

Our findings extend to a broader context. First, they are informative for the effects on patients who lose access to their physician due to other reasons than practice closures. These include, for example, discontinuities of care encountered by moving, or by other disruptions to the doctor-patient relationship. The latter is especially relevant in healthcare systems where insurers and providers are vertically integrated and therefore a change of the insurance plan can force patients to find a new provider, as is the case in the United States. Further, the results may also be informative for provider shutdowns in a more general context, for example, when pharmacies or food stores close (see the related literature on food deserts, e.g., Allcott et al., 2019).

The rest of this paper is structured as follows. Section 2 reviews the relevant literature. Section 3 provides some institutional background on our setting. Section 4 describes our data sources and the construction of the treatment and the control group. The descriptive analysis is presented in Section 5. Section 6 explains the empirical strategy. Section 7 reports the empirical results and discusses the main findings. Finally, Section 8 concludes.

2 RELATED LITERATURE

Availability of Primary Care. There is a considerable literature investigating the relationship between the local supply of primary care and various health outcomes of the population, see for example Starfield et al. (2005) and Shi (2012) for reviews. Most studies use regression methods to estimate the association of the primary care physician density (i.e., the physician-to-population ratio) with the outcomes of interest while controlling for a host of covariates such as socio-economic indicators and demographic composition. The physician density is typically measured on a regional level (e.g., county or state), while the outcome of interest may be measured on a more detailed level.

In a recent analysis, Basu et al. (2019) find that an increase of ten additional primary care physicians per 100,000 inhabitants is associated with a 51-day increase in life expectancy. This positive association between primary care supply and health outcomes is also supported by a number of other studies (Macinko et al., 2003; Shi et al., 2004; Laditka, 2004; Chang et al., 2011; Finkelstein et al., 2016). One exception is Ricketts and Holmes (2007) who report only a weak relationship between the primary-care physician density and mortality in the whole of the United States. Regarding the link between primary care supply and healthcare spending, the evidence seems less clear (Baicker and Chandra, 2004; Chernew et al., 2009). A few studies also focus on self-reported health status; they find that favorable assessments by individuals are positively associated with the local availability of primary care (e.g., Shi and Starfield, 2000; Gravelle et al., 2008).

It is important to note that the estimates in this literature must be viewed as *conditional correlations*, as causality is difficult to establish for several reasons. First, it is usually impossible to account for all relevant confounders in observational data; there are likely to be unobservables that are associated with both the outcomes (e.g. mortality) and the physician density. Second, inverse causality likely plays a role because the availability of primary care is affected by physicians' location choices and these choices, in turn, depend on local healthcare markets. In order to draw causal inferences, some form of *exogenous variation* in the availability of primary care is ultimately required. One example is Carrillo and Feres (2019), who exploit a physician distribution policy in Brazil to estimate substitution effects between physician and nurse visits in prenatal care. The evidence suggests that more physician visits at the expense of nurse visits have no measurable impact on infant health.[1] Two other notable example are Finkelstein et al. (2016) who use patient migration to isolate place-based factors, and Liebert and Mäder (2018), who use the expulsion of Jewish physicians by the Nazi government to investigate the effect of physician density on infant mortality.

Provider Closures. Closures of providers can serve as a quasi-experimental setting to estimate the causal impact of changes in the availability of care on patient outcomes and utilization. With regard to primary care practices, we are not aware of any existing literature that

[1] A related literature studies the effect of *access* to primary care, see, e.g., Bailey and Goodman-Bacon (2015) who use the rollout of Community Health Centers in the US to study the effect of access to primary care in poor communities on long-term health. They find that increased access is correlated with a reduced mortality risk.

investigates the effects of closures on patient outcomes.[2] In contrast, several studies leverage *hospital* closures and the induced changes in geographic distance to the nearest facility. For example, Buchmueller et al. (2006) examine the impact of hospital closures in Los Angeles County on patients' healthcare utilization and health outcomes. To identify causal effects, they use the changes in the distance from the patients' home to the nearest hospital. The authors find that increased distance significantly raises death rates from heart attacks and unintentional injuries, while death rates from other causes, where timely care is less critical, are not affected. Moreover, they document no effects on overall outpatient utilization, although patients tend to shift their usual source of care towards ambulatory practices in response to hospital closures. Avdic (2016) uses a similar identification strategy to estimate the effect of the spatial distance to the nearest emergency hospital on survival probabilities following an acute myocardial infarction (AMI). Using detailed administrative data from Sweden over a twenty-year period, the results show a substantial decrease in the survival probability when geographic access to emergency care deteriorates. Interestingly, the effect is not persistent over time, which may be partly explained by subsequent relocations of vulnerable patients living in the catchment of closed hospitals. Two related studies on Medicare patients in the United States exploit changes in the *driving time* to the nearest emergency department. Their difference-in-difference estimates show that longer driving time significantly increases mortality for patients suffering from an AMI (Shen and Hsia, 2012; Liu et al., 2014). By contrast, Hsia et al. (2012) find no significant impact of hospital closures on mortality. However, the average change in distance to the nearest emergency department was less than a mile and thus very small. In addition, the effects may be underestimated because only inpatient deaths are observed (i.e., excluding patients who die en route). Further, effects may vary regionally. Based on hospital closures in California, Gujral and Basu (2019) find that AMI-related inpatient mortality only increases after rural hospital closures, while no such effect is found in urban areas. Besides cardiovascular-related deaths, there is also some evidence from a case study that large-scale closures of obstetric units had a detrimental (but transitory) impact on maternal and infant health (Lorch et al., 2013). Similarly, two recent studies exploit a policy change in Texas that shut down nearly half of all abortion clinics, which also reduced the supply of women's healthcare. Using a difference-in-difference framework, they find that increased distance to the nearest clinic decreases not only abortion rates but also preventive care

[2] The only related work is a qualitative case study by Nidiry et al. (2008) who analyze patients' decisions following the relocation of their previous primary care provider. They find that patients remain considerably frustrated after the relocation, independent of their decision to visit their previous provider at the new location or to transfer to a new, more closely located provider.

such as Pap tests or mammograms (Lu and Slusky, 2016; Lindo et al., 2019).

Continuity of Primary Care. Since our paper focuses on discontinuities of care due to the closure of patients' regular primary care practice, we also contribute to the literature in health services research that deals with the role of interpersonal *continuity of care* in primary care.[3] The empirical literature generally finds that having a continuous doctor-patient relationship with a primary care physician is associated with decreased use of emergency departments of hospitals (Rosenblatt et al., 2000; Gill et al., 2000; Burge et al., 2003; Menec et al., 2005; Ionescu-Ittu et al., 2007; Hong et al., 2010), fewer avoidable hospitalizations (Cheng et al., 2010; Hansen et al., 2013; Nyweide et al., 2013) and lower mortality rates among elderly patients (Wolinsky et al., 2009; Leleu and Minvielle, 2013). In reviewing the literature, it is important to point out that most existing studies fail to isolate the *causal effects* of continuity of care. First, patients with high and low observed continuity of care may not be comparable in *unobserved* health-related dimensions (see e.g. Saultz and Albedaiwi, 2004). Second, causality can run in both directions: healthier patients may be more satisfied with their physician and therefore choose to remain in a more continuous doctor-patient relationship. As a result, selection on unobservables and simultaneity confound the analysis, so that it remains difficult to assess whether interpersonal continuity of care is, in fact, causing better outcomes.[4]

3 INSTITUTIONAL BACKGROUND

Mandatory Health Insurance. Switzerland has a comprehensive system of mandatory health insurance, which is modeled according to the principles of managed competition (Enthoven, 1978). Private health insurers compete on prices and quality and, similar to the Affordable Care Act (ACA) Marketplaces, patients may change their plan each year during an open enrolment period. Notably, insurers offering mandatory health insurance are obliged to accept all patients who wish to enroll in one of their contracts. Coverage is comprehensive and standardized and includes virtually all ambulatory services offered by medical doctors in the system, along with a comprehensive basket of pharmaceuticals, inpatient care, physiotherapy, and long-term care. Each insurer is obliged to offer the basic plan, which, for adults, features

[3] According to the American Academy of Family Physicians, continuity of care may be defined as "the process by which the patient and the physician are cooperatively involved in ongoing healthcare management toward the goal of high quality, cost-effective medical care" (cf. Gulliford et al., 2006).

[4] A notable exception is an ongoing clinical trial by the Comprehensive Care Group in Chicago that tests the implication of the comprehensive care model put forward by Meltzer and Ruhnke (2014). Rather than receiving inpatient care from hospital-employed physicians (hospitalists), treated patients get outpatient and inpatient care from the same doctor (comprehensive care physician). Note that this in turn increases the continuity of care. Results of a pilot study from 2012 to 2016 with 2,000 Medicare patients with chronic conditions show that the continuity of care could be improved. `https://www.nytimes.com/interactive/2018/05/16/magazine/health-issue-reinvention-of-primary-care-delivery.html`

a standard deductible of CHF 300. Once the annual deductible is exhausted, individuals face an additional co-payment rate of 10%, up to a stop-loss amount of CHF 700. Notably, the basic plan entails no mandatory gatekeeping mechanism, so that patients enjoy free physician choice among both GPs and specialists. Referrals are not required.[5] In exchange for a premium rebate, individuals can opt for a higher deductible (CHF 500, 1,000, 1,500, 2,000, 2,500), a more restrictive provider choice, or any combination of these two options. These restrictions are offered in the style of managed care health plans and include preferred-provider organizations (PPO), health maintenance organizations (HMO), and telemedicine plans (TelMed). The three types of plans mainly differ in what gatekeeping system they employ: The gatekeeper is either a general practitioner (PPO), a group practice or physician network (HMO), or a call center (TelMed) (cf. Schmid et al., 2018, for an overview).

Primary Care Market. General practitioners (GPs) are the most important source of ambulatory care (cf. De Pietro et al., 2015).[6] Most GPs are self-employed and work in solo or shared practices.[7] Large group practices (clinics) with salaried employment are less common, although their number is growing. The importance of GPs as primary care providers is reflected in the fact that during 2011, 67% of the adult population have visited a GP at least once[8] and most citizens report to have a regular GP (De Pietro et al., 2015). Ambulatory providers are (mostly) reimbursed under a Fee-For-Service schedule (Tarmed). The fees are regulated at the federal level, and a particular service is reimbursed identically for all physicians in the same canton and specialty (De Pietro et al., 2015).[9] While access to primary care is generally considered to be good (OECD and WHO, 2011), the GP density varies considerably among regions and tends to be lower in rural areas (De Pietro et al., 2015).

Primary Care Supply. In 2011, almost half of the GP workforce was above the age of 55 and likely to retire within the next 10 to 20 years (Gähler et al., 2013).[10] Inflow of new residents, both foreign-trained and medical students entering the profession, is deemed in-

[5] In 2006, 41% of the adult population were enrolled in the basic plan (standard deductible and no managed care feature) (FOPH, 2019). This is reflected in the relatively low referral rate of 9%. In a representative study of Swiss GPs, Tandjung et al. (2015) find that 91% of patient contacts are handled solely by GPs without referrals to other providers. Note that in recent years the share with the basic plan declined as managed care options became more attractive: 25% in 2011 and 20% in 2014 (FOPH, 2019).

[6] In the Swiss healthcare system, GPs are physicians who work in ambulatory practices and who hold one of the following specialty titles: *Allgemeinmedizin, Innere Medizin, Allgemeine Innere Medizin, praktischer Arzt/Ärztin* (English: general medicine, internal medicine, general internal medicine, medical practitioner).

[7] In 2014, 51% of all GPs worked in a solo practice (Senn et al., 2016). Among all physicians in ambulatory practices, including specialists, 84% own or co-own the practice they currently work in (Hostettler and Kraft, 2018).

[8] Swiss Health Survey 2012, Table G24, `https://www.bfs.admin.ch/bfs/de/home/statistiken/gesundheit.assetdetail.7586117.html`

[9] Exceptions prevail for HMO plans. Here, some physician networks accept complete financial responsibility for their patients, including inpatient and specialist care. These contracts are negotiated between insurance carriers and providers. Note that, contrary to the US, insurers and providers are typically not vertically integrated.

[10] While the composition of the GP workforce has changed in the meantime, in 2018 slightly more than half of the GP workforce was over the age of 55, and many providers keep working beyond the official retirement age of 65 (64 for women) (SMA, 2018).

sufficient so that the availability of primary care is expected to decrease. The potential supply shortage is further exacerbated by structural changes in the composition of the GP workforce. These changes include an increased desire for part-time work and a rising demand for salaried employment in a larger practice, which are both amplified by the feminization of the profession (Cohidon et al., 2015; Gisler et al., 2017). These factors aggravate the difficulty of finding a successor for a solo practice. In turn, this diminishing supply of primary care is faced with a growing demand for health services due to the increased health needs of an aging population (Senn et al., 2016).

When a self-employed GP wishes to leave her medical practice, for example due to retirement, she will usually try to find a successor to hand it over. When her practice is self-owned, this implies selling it to an interested party. Therefore, not only does the GP need to find a successor, but she also has to value her practice to justify the sales price. In order to find a buyer, the GP will typically place an advertisement in a widely-read trade magazine and on a specific online platform, both run by the Swiss Medical Association. Additionally, a variety of private firms and professional associations offer consulting services to assist in closing a sale and finding an appropriate sales price. Physicians are advised to start this process at least three years ahead of the desired retirement date but to refrain from telling their patients before signing a contract with their successor.

4 DATA

In this section, we describe the existing data sources and the collection of the practice closure data. Moreover, we explain how the patients are matched to providers and how the two samples of patients, the treatment group and the control group, are constructed.

4.1 Data Sources

Our primary source is register data from a large Swiss health insurer (CSS Insurance) and its subsidiaries with roughly 1.2 million individuals annually enrolled in health plans under the compulsory health insurance law. Our data covers the period 2005 to 2016 on a claims level for all individuals who were enrolled with the insurer for at least five consecutive years. For each individual, we have information on the year of birth, sex, nationality, zip code, and the language of correspondence. Regarding health insurance choice, we observe the deductible level, plan type (standard or managed care), insurance carrier, accident coverage, and contract duration. Moreover, we have information on chronic conditions based on pharmaceutical cost groups (PCGs). The dataset is supplemented by claims-level data, where we observe for each claim the provider, beginning and end of each treatment spell, cause of treatment[11] (illness or accident), the number of consultations, and expenditures by category (total, inpatient, outpatient, drugs, etc.).

Information on practice closures is not available in any existing data source. To gather the required information, we draw on two auxiliary sources. We use provider-level data on the monthly number of consultations from 2005 to 2016. This data is taken from the *Datenpool*, a national database on services covered by mandatory health insurance. Additionally, we extract address details and the provider type (physicians' specialty) from the Accounting Register of the Swiss health insurers *(German: Zahlstellenregister)*. Based on these data sources, 8,791 primary care providers were active in the ambulatory sector (self-employed GPs and group practices with salaried GPs) during the observation period.

4.2 Data Collection of Practice Closures

Our primary data collection on practice closures is based on a combination of exploiting information in existing data and conducting field research. In a first step, we identify *potential* practice closures by analyzing the patterns of each provider's monthly number of consultations over time. If the volume is observed to drop to (nearly) zero and remains (nearly) zero afterward, we refer to this event as an "activity stop". In total, we identify 2,023 activity stops. It is important to note that a provider is defined by her accounting ID number. An activity stop therefore means that we observe a sudden stop in the billing under this accounting ID number. It may occur in a range of situations: permanent or temporary closure, handover to a successor, organizational changes (merger with another practice or transformation from self-employment to salaried employment) or relocation to another canton. In other words, an activity stop is a necessary, but not a sufficient condition for a practice closure.

In a second step, we exclude cases for which it appears very likely that the practice was handed over or merged with another existing practice. To this end, we exclude cases for which we find other primary care providers at the same location (address level) who are active during the month of the activity stop, or during the twelve following months. Moreover, we rule out potential temporary closures (e.g. due to illness, parental leave or sabbaticals) by omitting cases where we observe any primary care activity at the same address within the first twelve months after the activity stop. Furthermore, since we are interested in long-standing doctor-patient relationships, we only include activity stops if the provider had been active

[11] Maternity-related claims are excluded.

since the start of our observation period. In a third step, we conduct field research in order to verify whether the remaining events were, in fact, practice closures and to rule out false positives. Each individual case was investigated using a combination of internet research (e.g. newspaper articles) and short telephone interviews. If possible, the retired GPs were directly contacted by phone. In other cases, municipal clerks (in the case of small towns) and residents living adjacent to the former practice address could provide the required information. A few cases proved difficult to verify, for example, if no contact details were available. If no substantive evidence could be gathered, the case was omitted from the study. In total, about 900 inquiries by phone were carried out (with usually multiple queries per case). As a result of the data collection, we have gathered a sample of 325 primary care physicians who closed their practice during the period from 2006 to 2015.

4.3 Construction of the Sample

Treatment Group. Using the terminology from the causal inference literature, patients who experienced the closure of their regular GP's practice during the observation period are referred to as the "treatment group". Since the basic health plan includes free choice of provider, patients' regular GP must be determined empirically by analyzing their visits to all primary care providers. First, patients are matched to GPs in the treated group based on any visits made during the two years preceding the closure date. Second, a match is only defined as the regular GP if the empirically observed doctor-patient relationship is sufficiently strong: We require patients to have at least 3 out of 4 primary care consultations with that GP.[12] Slight changes of this threshold are not critical since the average share of primary care visits made to the regular GP among selected patients is 98% (cf. Table I).

To make meaningful before-and-after comparisons, we select only patients who are enrolled with the insurer at least during two years before and two years after their regular provider's closure date.[13] Moreover, we only consider patients who are at least 18 years old at the time of the practice closure and we exclude those who move to another municipality after the closure date.[14]

Control Group. To study the effects of practice closures on utilization and outcomes, the analysis must be based on meaningful comparisons between the treatment group and a suitable control group. The control group should include patients who did not experience any

[12] As a result, about 12% of the patients are excluded.
[13] As an exception, we also retain patients who die after the closing date.
[14] The decision to move to another municipality is arguably unrelated to the practice closure of a GP, but moving clearly changes the local healthcare market for these patients. Since we prefer to hold the conditions of the local healthcare market constant, these patients are excluded.

changes in their regular source of primary care, but who are otherwise similar in their relevant characteristics. In defining the control group, it must be kept in mind that the treatment group is a non-random subset of the overall population. After all, not all individuals seek primary care within a two-year period, and among those, not all individuals are observed to have a regular GP. It is therefore essential that the same sampling criteria are applied when constructing the control group. First, the sample of primary care practices is restricted to those that were continuously in operation. To rule out changes in the activities among GPs, we additionally exclude those for whom we observe an activity stop of another provider located at the same address. Based on these criteria, there are 3,690 continuously operating primary care providers. Second, we assign a hypothetical (monthly) closure date to each of these providers to "mimic" the construction of the treated group. We do so by generating random draws with replacement from the empirical distribution of observed closure dates. This re-sampling procedure ensures that the two groups are well balanced in terms of calendar time and that we effectively eliminate potential seasonal differences. Figure 1 shows the distribution of closure dates for both groups. Finally, we apply the same procedure for determining a patient's regular GP as we do for the treatment group, and we apply the same selection criteria with respect to the period of enrollment, the minimum age and changes of residence.

– Insert Figure 1 about here –

Missing Values. Since the data is taken from registers, data quality is very good compared to, say, survey data. However, there are a few missing values for physician age and gender. For the treated group, we impute missing values by setting age to the official retirement age in the period of the practice closure (20 cases). For the control group, we omit those (35 cases). In addition, we drop one case in the treated group with a missing value for gender.

Panel Data Structure. Overall, our dataset comprises 210,464 individuals, including 12,960 treated patients. All variables are aggregated on a quarterly frequency and time is measured relative to the (pseudo-) closure date with $t = 0$ indicating the period of closure. Compared to higher frequencies (e.g. monthly), quarterly intervals are attractive because they are less noisy, lead to a more manageable computational burden and exhibit fewer seasonal patterns, while they still allow for studying dynamics in a meaningful way. We analyze the data for each patient in the two years preceding the closure (*pre-treatment period*) as well as in the three years following the closure (*post-treatment period)*.

5 DESCRIPTIVE ANALYSIS

In this section, we provide descriptive statistics of patient characteristics for the treatment and the control group. The analysis is complemented by graphical evidence of the evolution of selected outcomes over time for the two groups.

5.1 Descriptive Statistics

Descriptive statistics of all relevant variables measured in the *pre-treatment period* are presented in Table I for both the control and the treatment group. As is evident from the table, the two groups are comparable in demographic characteristics as well as health-related outcomes. On average, patients in our sample are around 57 years old, and we observe slightly more females than males in both groups. Roughly two thirds of each group are German-speakers, and a vast majority of 80% are Swiss citizens. Almost half of each group suffers from one or more chronic conditions, as measured by 24 PCG indicators. Among these conditions, the most prevalent ones are diabetes, hypertension, and acid reflux. More detailed information on the prevalence of these different conditions can be found in Table A.1 in the Appendix.

With regard to health plan choices, the basic plan featuring the standard deductible of CHF 300 and free physician choice has a market share above 40% in the whole sample. When deviating from the basic plan, individuals in both groups are slightly more likely to increase their deductible (40%) than to opt for a managed care feature, but the control group is more inclined to include a managed care feature. Among these features, the PPO model, which usually entails a GP as a gatekeeper, is by far the most prevalent, as it is chosen by a fourth of the patients. Overall, 70% of the patients are completely unrestricted in their physician choice.

The average patient has 2.5 medical consultations per quarter: He sees a GP 1.5 times, seeks specialist care 0.7 times[15], and frequents an outpatient facility of a hospital 0.4 times.[16] Virtually all GP visits are made to the regular provider (97%). Specialist visits are dispersed among the different specialties. A relatively large share thereof is with ophthalmologists ($\approx$ 22%) and obstetrician/gynaecologists (OB-GYN) ($\approx$ 13%), while the other specialties remain below 10%.

Additionally, 4% of patients are hospitalized and spend an (unconditional) average of half

[15] Specialists include all physicians in the ambulatory sector with a specialty other than those categorized as GPs.

[16] Hospital outpatient visits include visits to the emergency department as well as elective outpatient care (e.g. surgery without overnight stay).

a day per quarter in a hospital. Patients incur total healthcare expenditures (HCE) of roughly CHF 1,200 per quarter. CHF 500 fall to the ambulatory sector (half of which are incurred by GP and specialist visits, and a third by hospital outpatient care), CHF 300 are spent on prescription drugs, and CHF 280 are inpatient costs.[17]

Overall, we find that average outcomes and characteristics are similar across the two groups in most cases. This observation is related to the fact that the construction of the samples is based on the same set of criteria. As expected, the most pronounced difference prevails with regard to the characteristics of the regular GP: Physicians in the control group are younger, with an average age of 56 versus 63 in the treatment group. This age gap occurs *by design*, as the majority of practice closures are a result of retirement. Since the credibility of the econometric analysis is linked to the comparability of the two groups, an attractive strategy is to re-weight the control group to improve balance in the covariates (see Section 6). Descriptive statistics based on the re-weighted control group are shown in Tables A.2 and A.3. The re-weighting scheme achieves almost perfect balance in the means of the pre-treatment variables.

Finally, to assess the external validity of our results, it is interesting to compare some of the average characteristics of our sample to those of the adult population in Switzerland. For example, in 2011, the average age among the adult population was 48, average HCE in mandatory health insurance was CHF 3,684 (vs. annualized HCE of CHF 4,800 in our sample) and the hospitalization rate was 13% (vs. an annualized rate of 16% in our sample).[18] Thus, on average, the individuals in our sample are older and have increased healthcare needs compared to the Swiss population.[19]

– Insert Table I about here –

5.2 Graphical Evidence

Figure 2 provides first descriptive evidence for differences in selected outcome variables between the control and treatment group before and after practice closures. Each figure displays quarterly averages of the treatment and the control group (dots) and a smoothed curve

[17]The remainder of HCE fall on other ambulatory costs and long-term care (nursing homes and nursing care at home).

[18]Numbers refer to the year 2011. The census data is taken from the database STATPOP of the Swiss Federal Statistical Office, see https://www.pxweb.bfs.admin.ch. The data on HCE is obtained from the operator of the Swiss risk equalization scheme, see https://www.kvg.org/de/statistik-_content---1--1052.html. The number of hospitalized persons is taken from the Medical Statistics of Hospitals (2011) of the Swiss Federal Statistical Office, see https://www.bfs.admin.ch/bfs/de/home/statistiken/gesundheit/gesundheitswesen/spitaeler/patienten-hospitalisierungen.assetdetail.6406938.html

[19]This difference reflects the fact that we study a population with increased health needs and a stronger tie to their GP, as compared to the population as a whole. However, this is not an obstacle for the purpose of this study as we focus on the group that is most affected by a practice closure. See also the discussion in Subsection 4.3.

that is estimated with a local linear regression separately on each side of the discontinuity.[20]

Utilization Patterns The left panel of Figure 2 shows the evolution of utilization patterns around the (pseudo-) practice closures. It is evident from Subfigure (a) that the control group (black) visits GPs at a relatively constant rate before and after the pseudo closure. In contrast, we notice two aspects of the treatment group (red). First, GP visits are relatively constant in the pre-treatment period. However, as was already observed in Table I, the visits occur at a higher rate than in the control group. Secondly, GP visits fall sharply once the practice closes and remain at this lower level throughout the end of the observation period. Note that the small drop in GP visits in the control group at the discontinuity is related to the fact that, by design, we only consider patients who are observed to have a regular provider in the pre-treatment period, but this is innocuous to the estimation of causal effects.[21] We observe an opposing dynamic for specialist consultations: After the practice closure, specialist consultations increase sharply and seemingly persistently among the treated. On the other hand, and up to an overall positive time trend present across the two groups, visits in the control group remain largely unchanged. These findings suggest that, first, some patients may struggle to find a new regular GP, since average utilization drops substantially. Second, patients seem to shift their utilization from primary care towards more specialist care. This result hints at the effective gatekeeping role of having a continuous relationship with a regular primary care provider and is in line with the literature discussed in Subsection 2.

– Insert Figure 2 about here –

As a general observation related to Figure 2, it is worth pointing out that a positive time trend is found not only for specialist care but also for the hospitalization rate and overall HCE (see Figure A.2 in the Appendix). These trends may be due to two reasons. First, positive trends in a *fixed sample* of patients appear natural because the average health status deteriorates over time as patients are aging and as the share of patients with chronic conditions is increasing. Second, positive growth may reflect a broader trend of increasing utilization, independent of health, and consequently rising costs of the healthcare sector in Switzerland (cf.

[20] The period $t = 0$ is excluded from the estimation to omit potential anticipation effects from the pre-treatment trend.

[21] By focusing on patients with a regular GP, we naturally only consider those patients who have *at least one GP visit* in $t \leq 0$. This selection on the number of GP visits causes a small drop in the average number of GP visits in $t > 0$ because the number of visits may be zero in $t > 0$ but not in $t \leq 0$. It is crucial to note that this effect is innocuous for the estimation of causal effect because the selection of patients is entirely based on *pre-treatment* outcomes and because the selection rule is identical in both the treatment and the control group.

Köthenbürger and Sandqvist, 2017). These observations illustrate the importance of including a flexible time trend in the econometric model. Note that we do not find any clear evidence that practice closures affect hospitalizations and HCE.

6 EMPIRICAL STRATEGY

To study the causal impacts of practice closures on patients' utilization and outcomes, we employ a difference-in-difference approach, where the changes in patients' outcomes before and after the (pseudo-) practice closure occurs are compared between the treatment group and the control group.

Notation. Our analysis uses the potential outcomes framework (see Imbens and Rubin, 2015), in which each individual can be in one of two potential states, treated or untreated. In our case, the *treatment group* refers to those patients whose regular GP has shut down her practice at some point during the observation period. We denote the treatment indicator for individual i by $D_i \in \{0,1\}$. If the regular GP of person i closes her practice during the observation period, then $D_i = 1$, and otherwise $D_i = 0$. We define the *calendar* time period in which the regular GP of individual i closes her practice by C_i. For the treatment group, C_i is observed, and for the control group, C_i is generated by a random draw with replacement from the distribution of the treated group such that $F_{C|D=1} \approx F_{C|D=0}$, where $F_{C|D=d}$ is the cumulative distribution function (CDF) of C_i given $D_i = d$. We employ the notion of "event time" $t = (c - C_i)$, where c is calendar time, measured in quarters. That is, $t < 0$ are periods before the practice closure and $t > 0$ are periods after the practice closure. It is assumed that patients' outcomes are observed in regular intervals before and after the (hypothetical) practice closure, i.e., $t \in \{-T_{begin}, \ldots, -2, -1, 0, 1, 2, \ldots, T_{end}\}$. Each individual has two *potential outcomes* for each treatment state: $Y_{it}(0)$ if i has not been treated at time t, and $Y_{it}(1)$ if i has been treated at time t. We seek to identify the *average treatment effect on the treated*:

$$\tau = E[Y_{i,t>0}(1) - Y_{i,t>0}(0)|D_i = 1]. \tag{1}$$

This effect measures the average impact of the practice closure of patients' regular GP on the average outcome in the treatment group.

Identification. In the difference-in-difference framework, causal effects are identified from *changes* in individuals' outcomes over time. The crucial identifying assumption is that, in the absence of any practice closure, trends in patient outcomes would have been similar across treatment groups, conditional on individual heterogeneity. Formally, this *conditional parallel trends assumption* can be stated as follows (cf. Abadie, 2005):

$$E[\Delta Y_{it}(0)|\mu_i, D_i = 0] = E[\Delta Y_{it}(0)|\mu_i, D_i = 1], \tag{2}$$

where μ_i is a patient fixed effect that captures any (time-constant) observed and unobserved characteristics such as birth year, gender, socioeconomic status, chronic conditions, and so on. The strength of the difference-in-difference approach is that the identifying assumption is much weaker compared to cross-sectional settings since we do not require that we fully observe patients' health status. While the parallel trends assumption is fundamentally non-testable, we argue that it is very credible in our setting for at least two reasons. First, the occurrence of a practice closure is mainly a function of the physician's age and therefore represents an exogenous event that is not confounded with outcome dynamics. In other words, endogenous treatment assignment is not an issue. Second, even prior to re-weighting the control group, patients are very similar across groups in terms of their pre-treatment outcome dynamics and their observed characteristics (cf. Section 5.1). This provides additional reassurance that the identification strategy is credible.

Regression Model. As Angrist and Pischke (2008) show, the difference-in-difference framework can be cast into the following two-way fixed-effects model for panel data:

$$Y_{it} = \tau S_{it} + \alpha S_{i0} + \mu_i + \theta_t + \varepsilon_{it}, \tag{3}$$

where $S_{it} \equiv D_i \mathbf{1}(t > 0)$ is an indicator for treatment and $\mathbf{1}(\cdot)$ is the indicator function equal to one if the enclosed statement is true and zero otherwise. The average treatment effect on the treated is captured by the coefficient τ. If dynamic effects are of interest, the specification in (3) can be adjusted slightly in that the treatment effect is estimated separately for each year of the post-treatment period. The variable $S_{i0} \equiv D_i \mathbf{1}(t = 0)$ accounts for the possibility that there is a partial impact during and right before the practice closure due to anticipatory behavior by the patients, as they are likely to learn about the retirement of their GP prior to the event.[22] The time effects θ_t allow for a nonparametric trend and capture the fact that outcomes change over time as a fixed patient population is ageing and their average health status tends to deteriorate.[23] Note that we need not control for calendar time or seasonality since C_i is

[22] In addition, we account for the fact that the timing of the practice closure is determined empirically (see Subsection 4.2) and thus somewhat fuzzy. It is therefore sensible to exclude period $t = 0$ from the pre-treatment period.

[23] Since the population is fixed, the share of patients with chronic conditions, for example, exhibits a positive trend, which raises average utilization and costs over time.

identically distributed in the two treatment groups. Likewise, we need not control for C_i because any individual-specific effect is fully captured by μ_i. The model is estimated using the within-estimator (fixed effects estimator). Following the recommendations of Abadie et al. (2017), the standard errors are clustered on the level of treatment variation, i.e., the physician level.[24]

Inverse Probability Weighting. We combine the regression approach with inverse probability weighting (IPW). This approach is appealing because it further strengthens the credibility of the parallel trends assumption and thus improves the robustness of the analysis (see e.g. Zeng et al., 2010; Zhang et al., 2010; Bond and White, 2013; Marcus, 2013; van Hasselt et al., 2015; Han et al., 2017, for applications).[25] The procedure weights the controls such that they resemble the treatment group more closely, and consequently, increases the credibility of the counterfactual. To this end, we estimate the regression function (3) using weights

$$W_i = D_i + \frac{\hat{\pi}_\beta(X_i)(1 - D_i)}{1 - \hat{\pi}_\beta(X_i)}, \tag{4}$$

where $\hat{\pi}_\beta(X_i)$ is the estimated propensity score. In order to achieve a good balance, we use the covariate-balancing propensity score (CBPS) introduced by Imai and Ratkovic (2014) including a rich set of characteristics and pre-treatment outcomes.[26] This approach creates identical pre-treatment trends in the two groups (see Section B in the Appendix for a description of the estimation procedure). To ensure sufficient overlap of the two groups, it is important to trim observations with extreme values of the propensity score (see, e.g., Imbens, 2004; Millimet and Tchernis, 2009; Crump et al., 2009; Huber et al., 2013). We trim individuals with values of the propensity score outside of $m \leq \hat{\pi}_\beta(X_i) \leq (1 - m)$, with $m = 0.001$. Additionally, we exclude controls with a score below the minimum among the treated, and treated above the maximum of the controls (Dehejia and Wahba, 1999).

Finally, we note that a recently emerging literature points out a particular weakness of the two-way fixed effects model for the difference-in-difference design. Given variation in treatment timing and dynamic treatment effects, this estimator does not recover a sensible

[24] Two notes: First, the physician-clusters are determined by the usual GP of the pre-treatment period (see Section 4 for a description). Second, statistical inference is fully robust to individual serial correlation over time: the higher level of aggregation (physician) fully nests the patient clusters.

[25] Another strategy would be to combine the regression with propensity score matching instead of weighting. In our context, where the control group is much larger than the treated group, (pair-) matching is not attractive because only a small fraction of the control group is used for estimation. As a result, the variance of the matching-based estimator is substantially larger compared to variance of the weighting-based estimator.

[26] The characteristics include demographics, physician characteristics, and information on health plan choice. The pre-treatment outcomes include visits, hospitalizations, and costs. We distinguish between average quarterly outcomes for two time periods: First quarterly means for quarterly means of periods $t \in [-11, -4]$ and second for periods $t \in [-3, -1]$. See Section B in the Appendix for a full list of covariates.

average of the individual treatment effects (cf. Abraham and Sun, 2018; Athey and Imbens, 2018; Callaway and Sant'Anna, 2019; de Chaisemartin and D'Haultfœuille, 2018).[27] Our empirical setting does not suffer from this problem, because the analysis is conducted in event time, where the event occurs in the same period ($t = 0$) for all individuals.

7 RESULTS AND DISCUSSION

We first briefly comment on the implementation of the inverse probability weights discussed in Section 6. The weights produce almost perfect balance in the means of the covariates (including pre-treatment outcomes) across the two groups (see Table A.2). This balancing property is also illustrated in the evolution of visits in the right panel of Figure 2. For completeness, the density of the estimated propensity score is depicted in Figure A.3 in the Appendix.

In what follows, we present results from the estimation of the fixed-effects model using the quarterly panel dataset on individual patients. For each outcome variable, we estimate two models: first, the fixed-effects model in equation (3) and second, the enhanced specification with dynamic treatment effects. The former produces an *average* causal effect for the entire post-treatment period and the latter shows how the magnitude of the causal effect changes dynamically over the post-treatment period. Throughout the analysis, we use the inverse probability weights described in Section 6. Table II prints the results of our main specification for a wide range of outcomes. The results of the dynamic specification are shown in Table A.4 in the Appendix.

7.1 Utilization Patterns

Panel A in Table II shows the average causal effects of practice closures on quarterly visits to different types of healthcare providers. We first discuss the causal effects on the number of primary care (GP) visits and specialist visits. As was already evident in Figure 2, the number of visits to primary care providers fall sharply right at the shut-down of a practice $(t = 0)$. Importantly, patients affected by a practice closure show a significant decrease in the number of GP consultations by 0.18 per quarter, which amounts to -12% in relative terms. This effect is persistent and may even increase somewhat over time (cf. Table A.4). In contrast, we observe a clear causal impact on specialist visits in the opposite direction: the number of visits to these secondary-care providers increases by 0.07 or roughly 10%. These findings suggest that

[27] More specifically, the two-way fixed effects estimator produces a weighted average of the individual treatment effects where the weights can be negative. These negative weights mainly arise when treatment effects vary over time because already treated units sometimes act as controls (see Goodman-Bacon, 2018, for a decomposition of the weights).

patients adjust their utilization patterns considerably in response to the shutdown of their main source of primary care: they visit (new) primary care physicians less frequently than before, which is partly offset by an increase in specialist care. Here, it is not clear, however, whether more specialist care is induced by patients' own initiative or by their new primary care providers. Still, the causal shift of utilization patterns can be taken as evidence that patients' former GP exerted some influence as gatekeeper to other providers.

Selected Specialist Visits. To shed more light on the substitution patterns between primary and secondary care, we analyze consultations with selected physician specialties.[28] It is possible that patients choose a specialist as their primary care provider, e.g., many women in the United States view their gynecologist as their primary care provider (Mazzoni et al., 2017). As can be seen from Table II, no clear pattern emerges and most effects are imprecisely estimated due to low utilization rates. The only statistically significant effect is found for dermatologist visits. Taken together, this suggests that patients do not turn to a particular medical specialty to substitute GP care. However, the result also implies that patient frequent different doctors, which leads to more dispersed care.

Further, hospital outpatient visits increase by 0.019 per quarter, or roughly 5% (see Table A.4 for the dynamic specification), but this effect is only significant at the 10% level. Among other things, this variable includes visits to emergency departments. Therefore, the result lends itself to two interpretations. First, some patients affected by the shutdown of a primary care practice might use emergency departments as a *substitute* for scheduled visits to the GP because they struggle to find a new regular GP. Second, it is also possible that the discontinuity of care leads some patients to neglect certain health problems, for example, because a drug-related treatment or the regular monitoring of a chronic condition was discontinued. Exacerbated health problems might trigger the need for additional outpatient care at hospitals. In case of the latter, we would expect that an increase in hospitalization rates accompanies the increase in hospital outpatient visits as a fraction of patients is admitted to inpatient care departments.

While we observe a pronounced shift from primary care to specialist care, the drop in primary care consultations is not fully offset by the increase in specialist and hospital care: a practice closure reduces total visits by 0.09 (or 3.5%). Put differently, the shift results in nine fewer consultations per 100 patients and quarter. Therefore, the effect of primary care practice closures on the utilization of ambulatory services may be summarized as follows:

[28] These include the largest specialties in the ambulatory sector (OB-GYN, Psychiatrists, Dermatologists, Ophthalmologists, and Otorhinolaryngologists). For smaller specialties, average utilization rates are extremely low such that the effects would be estimated very imprecisely.

A disruption in primary care supply causes affected patients to seek medical care less often. When they see a doctor, however, they are less likely to see a GP and more likely to visit a specialist or the outpatient department of a hospital.

– Insert Table II about here –

7.2 Hospitalizations

Panel B of Table II shows that hospitalization rates are not significantly affected by practice closures. The same holds true for the intensive margin, as measured by the number of days spent in inpatient care (see Table A.4 for results of the dynamic specification). These effects are in stark contrast to the literature, which reports a significantly negative relationship between continuity of care (duration and intensity of the doctor-patient relationship) and hospitalizations (Cheng et al., 2010; Hansen et al., 2013; Nyweide et al., 2013). A possible explanation is that the results from previous studies merely measure conditional correlations. Indeed, existing studies are mostly based on observational data where selection effects and simultaneity both prevent the identification of causal effects.

Together with the results on the utilization pattern described in Subsection 7.1, the results on hospitalizations suggest that the uptick in hospital outpatient visits is not driven by a health neglect channel, as discussed previously. Rather, this finding points to non-urgent emergency department visits, i.e. that patients may, in fact, use hospital outpatient visits as a substitute for primary care visits.[29]

7.3 Healthcare Expenditures

Next, we consider the causal effects on patients' quarterly healthcare expenditures (HCE). Panel C in Table II shows that total HCE are not significantly affected by primary care practice closures. This result also holds for various cost categories: when they are broken down by different types of costs, only ambulatory costs transitorily increase significantly by CHF 23 per quarter (or 5%) in the first year after the closure (Table A.4).

Although we do not observe any relevant effects on total HCE, practice closures still have a potentially unfavorable effect on healthcare costs: The steady level of total HCE combined with the negative and lasting effect on visits implies an increase in the average cost *per visit*. In fact, the cost per visit increases by CHF 3.70 (5.6%) when only GP and specialist visits

[29]Note that we observe patients for up to three year after the closure. If adverse effects of a possible health neglect are only observable after, say, 10 years, the effect does not show up in our data. Still, we can rule out such an effect in the short and mid-run.

are considered, and by CHF 4.20 (4.8%), when costs incurred in hospital outpatient clinics are included. This is a direct consequence of the utilization shift described above: specialist care tends to be more expensive than GP visits and therefore the cost per visit increases. The implications of this increase, however, crucially depend on the types of visits: This growth in cost per visit is inefficient if, first, specialists offer the same services previously provided by GPs, or if, second, patients are in need of specialist care because they have neglected their health as a consequence of the practice closure.[30]

7.4 Health Plan Choice

The practice closure of the regular provider has a strong and lasting effect on patients' health plan choice. Panel D in Table II illustrates that the market share of PPO health plans decreases by 1.7 percentage points from a baseline of 27%. On the contrary, HMO plans nearly triple their market share, but the absolute increase is only 1.8 percentage points because the baseline is very low. The dynamic effects shown in Table A.4 suggest that these effects increase over time, which partially reflects a system-driven lag, as most patients can only adapt their health plan once a year during the open enrolment window. Depending on the calendar month of closure, patients may thus have to wait up to 11 months before they can change their contract a first time. It is noteworthy that patients do not revert to the standard plan with free provider choice. Rather, they alter their choice among the available managed care options. From a patient's perspective, HMO contracts often differ from PPO contracts simply by the fact that the gatekeeper is a (large) group practice or a provider network instead of a single provider. These results suggest that patients may have difficulties in finding a new regular provider and thus prefer to adapt their health insurance contract accordingly.

7.5 Heterogeneity Analysis

Thus far, the discussion has focused on the treatment group as a whole. However, the impact of losing the regular GP may well be different across patients who face different levels of availability of primary care and across groups of patients who differ in health-related or demographic characteristics. In this section, we investigate some potential sources of heterogeneity.

[30] On the other hand, the increase in the average visit costs may be efficient if patients receive more adequate care after the practice closure. For example, due to higher quality services or if previously underprovided patients only now receive the adequate level of care. These changes then reduce the future need of more extensive (and costly) treatments.

7.5.1 Availability of Primary Care

To analyze the relationship between the magnitude of causal effects and the degree of availability of primary care, we perform the analysis separately for a group of patients facing a high level of availability in their proximity and a group of patients facing a low level of availability. The first group consists of those patients whose local physician density lies above the 66th percentile of the physician density variable in the treatment group. Correspondingly, the second group are those patients below the 33rd percentile. We use a needs-adjusted inverse-distance weighted GP-to-population ratio to measure availability. A detailed description of the availability measure can be found in Section A in the Appendix.

Table III presents the estimates of the causal effects of practice closures on the outcomes studied in the previous sections separately for the two samples (low vs. high availability). In line with our expectations, the negative impact on GP visits is stronger for those patients who live in areas with relatively few primary care providers relative to the population. The average number of visits made to GPs falls by 14% in areas with low availability vs. a decrease by 11% in areas with high availability (overall sample: 12%). As expected, the degree of substitution to specialist care also depends on local availability. Specialist visits increase by more than 15% in well-served areas, while they increase by 6% in low-density regions (overall sample: 10%). Interestingly, hospital outpatient visits significantly increase by 10% in high-density areas, while no relevant effect is found for low-density areas. Further, ambulatory costs increase considerably by CHF 34 (or 7%) in high-density areas and overall visits decrease more strongly in low-density areas (-6%) but remain largely unaffected in high-density areas.

These results suggest that the local availability of primary care is an important mediator for the effects on utilization rates and costs. The results could imply that practice closures may foster inefficient utilization of ambulatory services, especially in high-availability areas, where patients usually have better access to alternative providers, including hospitals and walk-in clinics. On the other hand, patients in low-availability areas experience difficulties in finding a new regular GP. Given the (increasingly) uneven geographic distribution of healthcare providers in many countries, our findings have two implications for health policy. First, motivated by the potentially inefficient utilization pattern observed in areas with a high physician-to-population ratio, the *coordination* of primary care needs to be improved when patients lose their regular source of care. We note that in locations where access to care is seemingly not an issue, affected patients tend to seek care from different sources resulting in more fragmented care and possibly inefficient utilization. Encouraging patients to enroll in a gatekeeping health plan may narrow their clinical pathway and thus curb fragmentation. Further, assistance in transferring patients to new providers could improve medical care and potentially lower costs per visit. Finally, improving the clinical competence of pharmacists may be worthwhile. For example, triage at pharmacies could partially substitute missing primary care facilities in underserved areas and possibly improve patient-provider matching in high-density areas and thus alleviate pressure on the healthcare system.

Second, the results on regions with a low availability imply another important lesson for health policy: Health policy should promote a more evenly distributed supply of primary care doctors across regions. Practicing in the countryside may be incentivized, either through financial or structural incentives. Many medical professionals have voiced considerable frustration with the entrepreneurial side of running a solo practice, which also proves especially unattractive to young doctors (Gisler et al., 2017). Policy makers could actively encourage more attractive working conditions, especially in underserved areas, for example by helping to establish larger practices with salaried employment in remote areas. Financial incentives are already used in several countries, including the United States, Canada, and Germany. A widely used instrument to attract more junior physicians is to offer stipends or student loan relief to medical students who commit to practicing in an underserved region for a certain time period after graduation.[31] Another instrument that targets all GPs, irrespective of their career stage, includes the increased reimbursement of practitioners in underserved areas.[32] In Switzerland, a handful of municipalities at risk of becoming underserved provide active assistance, for example by funding the infrastructure of a group practice, which is often in the form of a Public-Private-Partnership.[33] Besides these discussed approaches, other possible financial instruments include tax deductions, favorable credit access, adjusting payments, and, perhaps most drastically, lump-sum transfers like they are commonly used in agriculture.

– Insert Table III about here –

[31] US: Public Student Loan Forgiveness for doctors (PSLF) administered by the US Department of Education, and State Loan Repayment Program (SLRP) offered by the National Health Service Corps (NHSC) both provide incentives for doctors to practice in federally designated *"health professional shortage areas"* (HPSA); Canada: In the Canada Student Loan Program (CSLP), the federal government offers $8,000 annually in loan forgiveness, up to a total of $40,000, for family doctors and family medicine residents who practice a minimum of 400 hours in designated remote communities. (https://www.ourcommons.ca/Content/Committee/421/FINA/Brief/BR9073035/br-external/CanadianFederationOfMedicalStudents-Loan-e.pdf); Germany: some states offer stipends such as the "Thüringen-Stipendium" or the "Landarztquote".

[32] US: NHSC's Centers for Medicare and Medicaid Services (CMS) provides millions of dollars annually in bonus payments to providers for services given in certain types of shortage designations. Rural Health Clinics (RHCs): NHSC designates certain shortage regions. These shortage designations allow certain clinics in rural areas to be certified by CMS as Rural Health Clinics (RHCs), providing enhanced reimbursement. These enhanced payments help to make RHCs economically sustainable. (https://bhw.hrsa.gov/shortage-designation/what-is-shortage-designation)

[33] Examples include the municipalities of Albula and Alvra (GR), Meisterschwanden and Seuzach, or Oberhasli (AG) (see https://www.srf.ch/news/schweiz/hausaerztemangel-selber-loesen-buendner-gemeinden-locken-hausaerzte-mit-anreizen-an, https://www.bernerzeitung.ch/region/oberland/aerztezentrum-oberhasli-seit-bald-neun-jahren-eine-erfolgsgeschichte/story/29980544).

7.5.2 Vulnerable Subgroups: Chronic Conditions and ACSCs

Patients with certain chronic conditions might be particularly vulnerable to disruptions in their primary care provision. Since our data does not include any direct information on diagnoses, we use binary indicators on 24 pharmaceutical cost groups (PCGs), which are based on prescription drugs (cf. Table A.1).

In a first step, we compare healthy patients to those who belong to *any* PCG. As anticipated, patients with a chronic condition as measured by the PCGs adapt their utilization pattern more strongly than healthier patients do (Table A.5). For example, we find an increase in hospital outpatient visits (7%) and a stronger boost in specialist visits (12%). As a result, the total number of visits is relatively less strongly affected compared to healthier patients. Still, due to the higher baseline, this translates to a decrease of 10 visits per 100 chronic patients and quarter. Overall, these findings suggest that those patients who are perhaps in most need of continuous primary care are still able to obtain medical support after they have lost their usual source of care. While this may not be cost-effective, our results show no evidence for an adverse effect on health, as indicated by hospitalizations.

In a second step, we focus on a group of conditions for which ambulatory care has been shown to play an important role in mitigating the course of disease. For these so-called Ambulatory Care Sensitive Conditions (ACSCs),[34] there is a strong link between timely ambulatory treatment and fewer avoidable hospitalizations (Bindman et al., 1995; Dafny and Gruber, 2005). We run separate regressions for all patients with a PCG linked to such an ACSC[35] and for the largest single ACSC available in our data: Diabetes and Hypertension. We focus on these two diseases because their prevalence is quite high such that the sample is large enough for the statistical results to be reasonably precise. For other diseases, the affected patient population is relatively small so that the lack of statistical power is an issue (see Table A.1 in the Appendix). Overall, the results are qualitatively similar to the results of the subsample with all chronic patients discussed above. However, the magnitude is often more pronounced for patients with an ACSC, as illustrated by Table A.6 in the Appendix. Both hospital outpatient visits and specialist visits increase strongly by 12% and 15%, respectively (11% and 17% for Diabetes, Hypertension). In turn, total visits are not significantly affected. Further, ambu-

[34] Billings et al. (1993) define these as "diagnoses for which timely and effective outpatient care can help to reduce the risks of hospitalization by either preventing the onset of an illness or condition, controlling an acute episodic illness or condition, or managing a chronic disease or condition".

[35] Our definition of ACSCs is based on Purdy et al. (2009). The authors start from the group of conditions used in practice by the National Health Service (NHS) and complement them with another set of conditions that are widely used in the literature. The PCGs include Asthma, Cardiovascular Diseases, Diabetes Type 1, Diabetes Type 2 (with and without Hypertension), High Cholesterol/Hypertension, and COPD.

latory costs increase by 6% (CHF 43) for the ACSC-subgroup. This increase is much more pronounced than for the broader group of all chronic patients discussed above. Perhaps surprisingly, we find no significant increase in hospitalizations for the ACSC-subgroup. This result also suggests that while patients may turn to less efficient sources of ambulatory care, there are no measurable health effects during our observation period.

7.5.3 Patient Characteristics

Last, we analyze how effects differ for population subgroups depending on health plan, age, and gender. The estimates discussed below are shown in Tables A.7 to A.9 in the Appendix.

PPO plans. We split the sample based on pre-treatment plan choice and perform a separate analysis for PPO enrollees. In a PPO model, patients are *obliged* to visit their regular GP first. There are two potential effects: First, because patients in a PPO model may have a higher intensity of continuity of care, changing their regular provider may have a stronger adverse impact on them. Second, when their regular provider shuts down, their insurance contract requires them to find a new gatekeeper, which in turn mitigates the effect of a practice closure. The main effects of practice closures are more pronounced for patients in the PPO plan (Table A.7). Compared to patients in all other insurance plans, those in PPO plans show a stronger increase of specialist visits (14% vs. 9%), and GP visits decrease by less (-10% vs. -13%). This leads to an overall smaller decline in total visits (not significant). Further, hospital outpatient visits are unaffected, unlike for patients in other plans (+7%).

Age. Based on the literature, we would expect a stronger adverse effect on older patients (cf. Rosenblatt et al., 2000; Ionescu-Ittu et al., 2007). Surprisingly, most effects are similar for patients above and below age 65 (Table A.8). This finding is in contrast to the previous literature, which has found more pronounced effects of continuity of care for elderly patients.

Gender. Practice closures may have different effects on men and women due to gender-specific patient behavior. We find a gender difference in the substitution pattern of visits. In particular, men increase their specialist consultations by more (13% vs. 8.5%). On the other hand, total visits only decrease for women (Table A.9).

8 CONCLUSION

This paper has examined how patients are affected when their regular primary care physician closes down her practice, typically due to retirement. Our empirical strategy is based on a difference-in-difference framework in which patient outcomes are compared before and after practice closures between a treatment group and an unaffected, but comparable, control group. We have exploited rich insurance claims data on more than 210,000 patients that have allowed us to study consultation patterns, hospitalizations, healthcare expenditures, and insurance choice.

We find robust evidence that patients significantly adjust their utilization behavior after their regular GP has closed her practice. First, as expected, the number of visits to GPs falls significantly. Second, this reduction is partially offset by an increase in visits to specialists and hospital outpatient facilities (including emergency departments). In contrast to the literature on interpersonal continuity, we find no increase in the hospitalization rate. Further, practice closures increase the cost per visit but do not affect total healthcare expenditures due to the reduction in visits per patient. Finally, the disruption in care induces patients to switch to health plans with more lenient gatekeeping. The changes in utilization patterns may have two underlying explanations. First, adjustments in utilization may reflect changes in health that are caused by interruptions in care, for example, neglect of preventive care, medication adherence, or the monitoring of chronic conditions. However, the results on hospitalizations suggest that at least in the short run this is not the case. Second, it is also plausible that the response of patients is (at least partly) behavioral. That is, patients fail to establish a comparable relationship with a new primary care provider and shift their utilization towards other sources of care. Overall, our results point to the second channel.

We also document important heterogeneous effects across different groups of patients. Most notably, patients with chronic conditions (almost) maintain the number of overall visits after they lose their regular GP by strongly shifting visits towards specialists and outpatient departments of hospitals. In contrast, we find no evidence that health-related outcomes are significantly negatively affected, as far as HCE and the hospitalization rate are informative. Another important dimension of heterogeneity is the local availability of primary care. In areas with few GPs relative to the population, the reduction in total visits to doctors and hospitals is much more substantial. This disparity indicates that patients forgo primary care because they struggle in finding a new regular GP. In high-availability areas, patients tend to substitute with specialist care and hospital outpatient care.

The findings presented in this paper may be relevant from the perspective of health policy and healthcare planning. First, the evidence implies that practice closures may cause a more inefficient use of healthcare services, as patients substitute GP visits with other sources of care. In particular, a rise in hospital outpatient consultations, which are typically considered less cost-effective, points in this direction. The increasing costs per visit also reflect this tendency.

Second, closures decrease access to primary care services in areas with low physician supply and therefore may cause patients to forgo primary care. Given the age structure of active GPs and the insufficient inflow of residents, policies should focus on the future supply of GPs and on a more equal geographic distribution.

Since our data carries no information on health outcomes of patients, insights on the health effects of practice closures are limited to indirect evidence. It is left for future research to investigate potential implications on patient health, especially in the long term. Another attractive avenue for future research is to explore the role of physician practice style when patients must transfer to a new GP. Such changes could, for example, be proxied by the age gap between the new and the previous GP. Finally, evaluating the success of different policy instruments targeted at young GPs to take over private practices from retiring GPs deserves further attention.

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Appendix

A Local Availability of Primary Care Services

To study the role of availability of primary care, we construct a location-specific primary care physician density. The numerator is an estimate of full-time equivalent GPs within a certain spatial distance from the location of interest. The denominator is an estimate of the population within the same spatial distance from the location of interest. The population is *needs-adjusted* by taking into account the demographic composition. If the demographic mix implies above-average needs for primary care, the population is adjusted upward. The adjustment improves the comparability of the physician density across high-need and low-need areas. Moreover, the density is calculated using *inverse-distance weighting*, that is, providers and population close to the location get a larger weight than those that are more remote. We calculate the measure for each year, but we omit the time subscript below for ease of notation.

It is worth noting that the approach is similar to the two-step floating catchment area (2SFCA) approach, which is often used to measure healthcare accessibility (Luo and Wang, 2003; Luo and Qi, 2009, for an extended version). To be consistent with our empirical analysis, we use the patient's place of residence as the reference point for the calculations, while the 2SFCA uses the physician's location. Two further differences are that (a) we additionally adjusts the population size by a measure of healthcare needs, and (b) we use a distance decay function to account for the fact that providers closer to the patient's residence are more important than more remote providers.

The needs adjustment is performed using age- and gender-specific primary care utilization rates. Denote by $Pop_{h,g,1000}$ the population (in thousands) on hectare $h \in \mathcal{H}$ (100×100 meters) in gender-age group $g \in \{1, ..., G\}$, $UR_{c(h),g}$ is the per-capita utilization rate in group g and in the canton c of hectare h, and $UR_{c(h)}$ is the overall per-capita utilization rate in the canton of hectare h.[36] The needs-adjusted population, $AdjPop_h$, is then calculated as follows:

$$AdjPop_h = \sum_{g=1}^{G} AdjPop_{h,g} \, ,$$

with

$$AdjPop_{h,g} = Pop_{h,g,1000} \left(\frac{UR_{c(h),g}}{UR_{c(h)}} \right) .$$

The adjustment factor is proportional to the group-specific utilization rate and is normalized

[36] Switzerland is a federal state, consisting of 26 cantons.

such that the total observed and adjusted population counts on the cantonal level are equal, i.e., $\sum_{h:h(c)=c} AdjPop_h = \sum_{h:h(c)=c} Pop_{h,1000}$. To provide some intuition, suppose that the utilization rate for males aged 66 to 70 is 6 versus an overall utilization rate of 4 within a given canton. Then, the adjusted population of this age-gender group is 1.5 times the observed population. In other words, individuals in this age-gender group are assigned a larger-than-average weight when aggregating the population counts because their utilization rate is above average.

Moreover, denote by FTE_i the number of full-time equivalent GPs of provider $i \in \{1, ..., N\}$. Let $d(a, b)$ denote the distance function for two spatial points a and b and define $\mathbf{1}(\cdot)$ as the indicator function which is equal to one if the argument in parentheses is true and zero otherwise. The adjusted population count and the FTEs for location l within a radius of r kilometers are:

$$AdjPop_{l,r} = \sum_{h \in \mathcal{H}} \mathbf{1}\big(d(l,h) \leq r\big) \cdot AdjPop_h$$

$$FTE_{l,r} = \sum_{i=1}^{N} \mathbf{1}\big(d(l,i) \leq r\big) \cdot FTE_i$$

The primary care physician density within a radius of r kilometers around location l is given by:

$$DENS_{l,r} = \frac{FTE_{l,s}}{AdjPop_{l,s}}$$

To take into account that providers closer to l are more important than more remote providers for residents in location l, we aggregate the densities for the radii $r \in \{1, ..., R\}$ using inverse distance weighting:

$$DENS_l = \sum_{r=1}^{R} \omega_R(r) DENS_{l,r}$$

where the kernel function is defined as follows:

$$\omega_R(r) = \begin{cases} \frac{R-r+1}{\sum_{q=1}^{R} R-q+1} & \text{for } r \leq R \\ 0 & \text{otherwise.} \end{cases}$$

We use a simple triangular kernel because it is well suited for discrete data. In practice, the calculations are implemented as follows. We set the maximum radius (R) to 8 kilometers. This choice is motivated by the fact that Switzerland is very densely populated with small distances between municipalities. A location l is defined by the central coordinates of a zip code *and* a town name. In total, our data contains patients who live in 4,108 distinct locations.

The data is obtained from several sources. First, the spatial population data by age and gender (hectare level) is made available by the Swiss Federal Statistical Office. Second, primary care utilization rates (visits) by canton, age group (five-year intervals) and gender are extracted from the *Datenpool* of the Swiss health insurers for the year 2015.[37] Third, FTEs or hours worked are, unfortunately, not available on the provider level.[38] To obtain a rough estimate, we use the total number of visits at each provider as a proxy for imputing FTEs. To achieve this, we map the distribution of visits to a distribution of FTEs using simple threshold rules that are chosen such that the total number of estimated FTEs matches the number reported in the official statistics of the Swiss Medical Association.[39]

Figure A.1 illustrates the distribution of the location-specific primary care physician density on a map of Switzerland for the year 2015.

– Insert Figure A.1 about here –

[37] We use time-constant utilization rates because intertemporal variation should not influence the calculations.

[38] The Swiss Medical Association collects data on days worked per week from their members. However, this data is proprietary. In addition, it would be difficult to merge this data to the insurer data due to different identification variables.

[39] To be more precise, we use the following mapping: $FTE = \{[Q_{vis}(0.55); Q_{vis}(0.8)] \rightarrow 1; vis > Q_{vis}(0.8) \rightarrow Vis/Q_{vis}(0.8); vis < Q_{vis}(0.55) \rightarrow vis/Q_{vis}(0.55)\}$, where $Q_{vis}(\tau)$ is the τ-quantile of the distribution of visits on the provider level.

B Covariate-Balancing Propensity Score (CBPS)

We weight the control group such that the first moment of their (weighted) covariate distribution matches with that of the treatment group. The weights take the form of inverse probability weights for the ATT, using the propensity score. Balance is ensured by the chosen specification of the propensity score. Following Imai and Ratkovic (2014), we simultaneously maximize covariate balance and predict treatment assignment to obtain the covariate-balancing propensity score (CBPS).

We parametrize the propensity score $\pi_\beta(X_i)$ using a logit form including pre-treatment characteristics and outcomes (X_i).

$$\pi_\beta(X_i) \equiv Pr(D_i = 1|X_i) = \frac{\exp(X_i'\beta)}{1 + \exp(X_i'\beta)}$$

We can build inverse probability weights using the propensity score π_β. Applying these weights yields the following set of covariate-balancing moment conditions:

$$g_\beta(D_i, X_i) = E\left\{D_i X_i - \frac{\pi_\beta(X_i)(1 - D_i)X_i}{1 - \pi_\beta(X_i)}\right\} = 0$$

And an estimate for β can be obtained from GMM Estimation:

$$\hat{\beta}_{GMM} = arg \min_{\beta \in \Theta} \bar{g}_\beta(D, X)^T \Sigma_\beta(D, X)^{-1} \bar{g}_\beta(D, X)$$

, where $\bar{g}_\beta(D, X) = \frac{1}{N}\sum_{i=1}^N g_\beta(D_i, X_i)$ is the sample mean of the moment conditions, and $\Sigma_\beta(D, X)$ is a consistent estimator of $var(g_\beta(D_i, X_i))$. Following the paper, our choice for $\Sigma_\beta(D, X)$ is:

$$\begin{aligned}\Sigma_\beta(D, X) &= \frac{1}{N}\sum_{i=1}^N E\left\{g_\beta(D_i, X_i) g_\beta(D_i, X_i)^T | X_i\right\} \\ &= \frac{1}{N}\sum_{i=1}^N \left(\frac{N^2 \pi_\beta(X_i)}{[N_1^2\{1 - \pi_\beta(X_i)\}]} X_i X_i^T\right)\end{aligned}$$

, where N_1 is the number of treated units.

Besides pre-treatment characteristics, the covariate vector X additionally includes pre-treatment outcomes. This produces identical pre-treatment time trends. The characteristics include demographics, physician characteristics, and information on health plan choice. The pre-treatment outcomes include visits, hospitalizations, and costs. We distinguish between two different time intervals for the outcomes: quarterly means for $t \in [-11, -4]$ and for $t \in [-3, -1]$.

The full set of included variables is a follows:

The characteristics include: *demographics* (age, sex, language of correspondence (dummy), nationality (dummy), NUTS-2 region (6 dummies), PCG dummies, provider continuity, GP density); *physician characteristics* (physician age (10-year categories), physician sex); *health plan choice* (accident coverage, deductible level (2 dummies), managed care contract (3 dummies), insurance carrier (3 dummies)).

The pre-treatment outcomes are measured for the two time intervals $t \in [-11, -4]$ and $t \in [-3, -1]$ and include: *visits* (total visits, GP visits, specialist visits, visits with selected specialists (Ophthalmologist, Gynaecologist, Psychologist Dermatologist, Otorhinolaryngologist), hospital outpatient visits, emergency visits); *hospitalizations* (inpatient days, hospitalization rate); *HCE* (total HCE, ambulatory costs, drug costs, hospital outpatient costs, inpatient costs).

C Tables and Figures

C.1 In-Text Tables

Table I: Descriptive Statistics, $t < 0$ (unweighted)

	Controls		Treated	
	mean	sd	mean	sd
Utilization				
Visits at Regular GP	1.299	2.161	1.437	2.291
Total Visits	2.422	3.424	2.550	3.504
GP Visits	1.349	2.229	1.484	2.367
Specialist Visits	0.689	1.733	0.672	1.718
Ophthalmologist Visits	0.138	0.612	0.145	0.627
OB-GYN Visits	0.098	0.491	0.086	0.438
Psychiatrist Visits	0.087	0.814	0.063	0.694
Dermatologist Visits	0.057	0.407	0.056	0.431
Otorhinolaryngology Visits	0.035	0.309	0.037	0.322
Hospital Outpatient Visits	0.383	1.200	0.393	1.205
UPC (Primary Care)	0.976	0.055	0.977	0.054
Hospitalization				
Inpatient Days	0.529	4.374	0.543	4.560
Hospitalization Rate	0.040	0.197	0.042	0.200
Costs (CHF)				
Total HCE	1,187.912	3,086.658	1,238.256	3,530.079
Ambulatory Costs	483.036	1,119.344	486.010	1,190.780
Visits Costs	238.349	485.155	235.918	509.702
Drug Costs	301.660	1,147.817	324.191	1,978.152
Hospital Outpatient Costs	135.905	832.126	145.519	910.144
Inpatient Costs	263.691	2,044.453	277.079	2,010.165
Patient Characteristics				
Age	56.163	18.545	58.619	18.102
Female (Share)	0.556		0.531	
German-Speaking (Share)	0.677		0.679	
Swiss Citizen (Share)	0.776		0.785	
Chronic Condition (Share)	0.431		0.451	
No. of PCGs	0.724		0.762	
Central Switzerland (Share)	0.157		0.170	
Espace Mittelland (Share)	0.217		0.346	
Northwestern Switzerland (Share)	0.148		0.097	
Eastern Switzerland (Share)	0.138		0.111	
Ticino (Share)	0.051		0.025	
Physician Density (8km)	0.751	0.754	0.738	0.410
Distance to Regular GP (km)	5.109	9.248	4.851	8.754
Health Plan Choice				
Basic Plan (Share)	0.422		0.450	
Medium Deductible (Share)	0.228		0.234	
High Deductible (Share)	0.179		0.162	
PPO Health Plan (Share)	0.269		0.274	
HMO Health Plan (Share)	0.050		0.011	
TelMed Health Plan (Share)	0.009		0.010	
Accident Coverage (Share)	0.613		0.638	
Physician Characteristics (Regular GP)				
Age	55.950	6.591	63.527	6.217
Female (Share)	0.110		0.073	
Patients		197,504		12,960

Notes: This table reports quarterly means for the pre-treatment period of all patients in our baseline sample assigned to the control group and the treatment group. Treatment group status is determined by a discontinuity in care of the regular primary care provider. Time is measured in event time, relative to a practice closure. Means are calculated based on two years before the treatment event. All costs are measured in CHF. Base category for 'region' is Zurich (numbers not displayed). 'Basic Plan' is a health plan with the standard deductible (CHF 300) and the standard model (free provider choice). Deductible levels are grouped into three categories: Small (CHF 300, numbers not displayed), Medium (500, 1,000), High ($\geq$ 1,500). Base category for 'health plan type' is Standard (numbers not displayed). Chronic conditions are measured by PCGs. UPC (primary care) measures the share of all primary care visits with the regular GP (usual provider continuity, UPC).

Table II: Causal Effects on Selected Outcomes

	Estimate	SE	in %	Baseline
A. Utilization:				
GP Visits	−0.175 ***	(0.032)	−11.8%	1.48
Specialist Visits	0.070 ***	(0.016)	10.4%	0.67
Hospital Outpatient Visits	0.019 *	(0.011)	4.9%	0.39
Total Visits	−0.086 **	(0.040)	−3.4%	2.55
Ophthalmologist Visits	0.005	(0.004)	3.6%	0.14
OB-GYN Visits	0.005	(0.004)	6.1%	0.09
Psychiatrist Visits	0.004	(0.006)	5.6%	0.06
Dermatologist Visits	0.007 ***	(0.002)	11.6%	0.06
Otorhinolaryngology Visits	0.001	(0.002)	3.6%	0.04
B. Hospitalization:				
Hospitalization Rate	0.002	(0.001)	3.6%	0.04
Inpatient Days	0.034	(0.032)	6.3%	0.54
C. Costs:				
Total HCE	19.971	(25.950)	1.6%	1,238.26
Ambulatory Costs	11.244	(10.785)	2.3%	486.01
Visits Costs	2.267	(5.469)	1.0%	235.92
Drug Costs	5.071	(9.210)	1.6%	324.19
Hospital Outpatient Costs	3.135	(7.317)	2.2%	145.52
Inpatient Costs	6.765	(13.448)	2.4%	277.08
HCE per Visit (GP/Specialist)	3.699 ***	(1.378)	5.6%	65.92
HCE per Visit	4.203 ***	(1.571)	4.8%	87.34
D. Health Plan Choice:				
PPO Health Plan	−0.017 **	(0.007)	−6.3%	0.27
HMO Health Plan	0.018 ***	(0.005)	169.8%	0.01
TelMed Health Plan	0.002	(0.002)	16.2%	0.01
Observations				4,065,938
Patients				210,464

Notes: This table shows weighted estimates of causal effects of practice closures on outcomes, i.e., the coefficients of the interaction between the treatment group and post-treatment periods. The model includes patient fixed effects and time effects. Data is measured in quarterly terms. Standard errors are clustered at the physician level.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

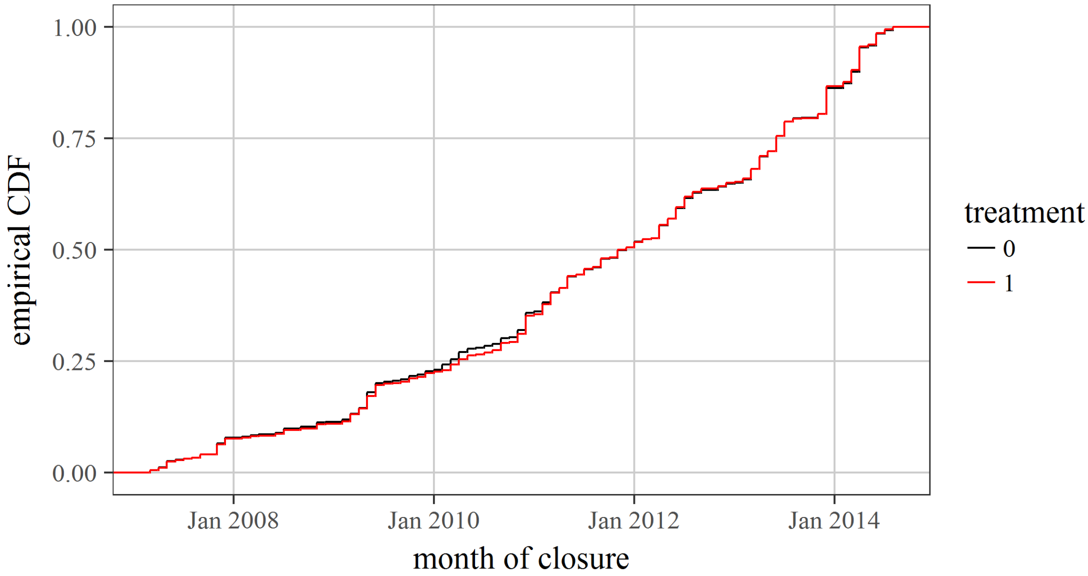
Table III: Causal Effects on Outcomes by Availability of Primary Care

	Low GP Density				High GP Density			
	Est.	SE	in %	Baseline	Est.	SE	in %	Baseline
A. Utilization:								
GP Visits	-0.187^{***}	(0.043)	−13.7%	1.37	-0.170^{***}	(0.045)	−10.7%	1.59
Specialist Visits	0.040^{*}	(0.021)	6.1%	0.66	0.102^{***}	(0.029)	15.2%	0.67
Hospital Outpatient Visits	0.006	(0.018)	1.6%	0.39	0.040^{**}	(0.016)	10.0%	0.40
Total Visits	-0.141^{**}	(0.060)	−5.8%	2.41	−0.029	(0.053)	−1.1%	2.65
Ophthalmologist Visits	0.002	(0.006)	1.3%	0.13	0.009	(0.007)	5.7%	0.15
OB-GYN Visits	0.006	(0.005)	7.0%	0.08	0.005	(0.005)	6.2%	0.08
Psychiatrist Visits	−0.006	(0.009)	−12.0%	0.05	0.005	(0.009)	7.4%	0.06
Dermatologist Visits	0.010^{***}	(0.004)	19.1%	0.05	0.004	(0.004)	7.9%	0.06
Otorhinolaryngology Visits	−0.001	(0.003)	−3.6%	0.04	0.005	(0.003)	12.4%	0.04
B. Hospitalization:								
Hospitalization Rate	−0.000	(0.002)	−0.2%	0.04	0.002	(0.002)	4.2%	0.04
Inpatient Days	0.050	(0.044)	10.4%	0.48	−0.021	(0.048)	−3.4%	0.62
C. Costs:								
Total HCE	13.175	(43.694)	1.1%	1,236.10	12.428	(37.938)	1.0%	1,274.68
Ambulatory Costs	−14.506	(18.116)	−2.9%	494.17	33.777^{**}	(15.747)	7.0%	485.07
Visits Costs	−8.524	(8.710)	−3.7%	232.10	8.106	(7.558)	3.4%	237.80
Drug Costs	22.637	(21.862)	6.7%	337.54	−0.796	(10.901)	−0.2%	325.60
Hospital Outpatient Costs	−8.786	(12.312)	−5.4%	161.91	15.819	(11.404)	11.4%	138.71
Inpatient Costs	14.323	(21.407)	5.4%	263.57	−20.283	(19.675)	−6.8%	299.22
D. Health Plan Choice:								
PPO Health Plan	-0.017^{**}	(0.009)	−6.5%	0.27	−0.016	(0.010)	−6.1%	0.27
HMO Health Plan	0.013^{**}	(0.006)	179.4%	0.01	0.017^{***}	(0.006)	117.2%	0.01
TelMed Health Plan	0.003	(0.003)	27.4%	0.01	0.001	(0.003)	8.5%	0.01
Observations				1,352,788				1,355,698
Patients				69,980				70,285
Patients (Treated)				4,494				4,728

Notes: This table shows weighted estimates of causal effects of practice closures on outcomes, i.e., the coefficients of the interaction between the treatment group and post-treatment periods. The model includes patient fixed effects and time effects. Data is measured in quarterly terms. Standard errors are clustered at the physician level.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

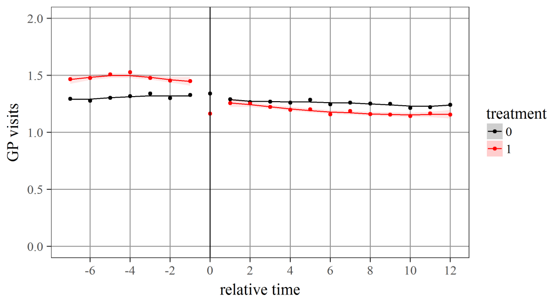
C.2 In-Text Figures

Figure 1: Distribution of Closing Dates

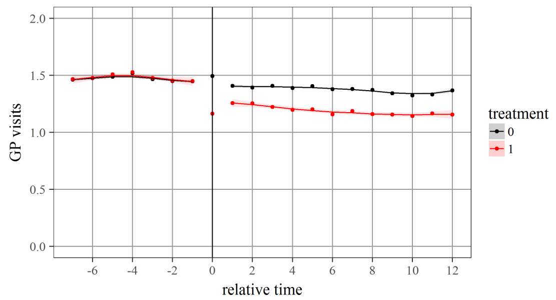


Notes: The figure displays the empirical cumulative distribution function (CDF) of the closing dates of the regular provider of primary care for the treatment group (red) and the control group (black).

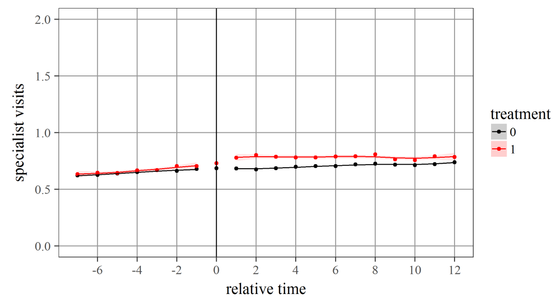
Figure 2: Utilization Patterns: Visits by Type of Doctor (GP and Specialists)



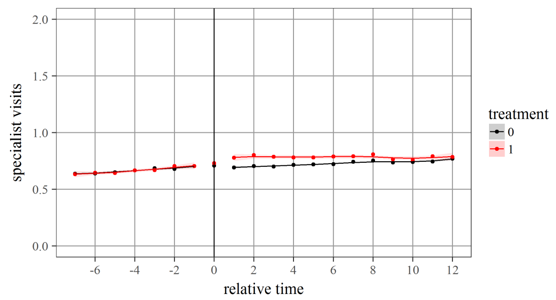
(a) GP Visits



(b) GP Visits, weighted



(c) Specialist visits



(d) Specialist visits, weighted

Note: Dots correspond to quarterly averages (right panel: weighted quarterly averages) and the smoothed curve is based on a local linear regression using a triangular kernel and a bandwidth of 3. The shaded areas are 95%-confidence intervals. Event time indicates the quarter relative to the event of the practice closure (at $t = 0$).

C.3 Additional Tables

Table A.1: Descriptive Statistics: Prevalence of PCGs (shares), $t < 0$ (unweighted)

	Controls	Treated
	mean	mean
Asthma, Respiratory Diseases	0.046	0.048
COPD	0.007	0.008
Epilepsy	0.011	0.012
Rheumatism, Rheumatoid Diseases	0.050	0.053
Cardiovascular Disease	0.039	0.048
Crohn's Disease, Ulcerative Colitis	0.005	0.005
Acid Reflux	0.129	0.131
Type 1 Diabetes (Mellitus)	0.007	0.007
Type 2 Diabetes (no Hypertension)	0.014	0.015
Type 2 Diabetes with Hypertension	0.048	0.054
High Cholesterol, Hypertension	0.094	0.107
Parkinson's Disease	0.008	0.009
Transplant	0.001	0.001
Malignant Tumor	0.020	0.022
HIV, AIDS	0.002	0.001
Kidney Disease (incl. end-state)	0.002	0.002
Glaucoma	0.040	0.046
Thyroid Disease	0.045	0.044
Osteoporosis	0.025	0.027
Migraine	0.009	0.008
Depression, Anxiety, OCD	0.098	0.091
Chronic Psychosis	0.009	0.007
Addiction (Alcohol, Heroin)	0.004	0.004
Alzheimer's	0.004	0.003
Neuropathic Pain	0.006	0.005
ADHD	0.002	0.001
Patients	197,504	12,960

Notes: This table reports quarterly means for the pre-treatment period of all patients in our baseline sample assigned to the control group and the treatment group. Treatment group status is determined by a discontinuity in care of the regular primary care provider. Time is measured in event time, relative to a practice closure. Means are calculated based on two years before the treatment event. Chronic conditions are measured by pharmaceutical cost groups (PCGs).

Table A.2: Descriptive Statistics, $t < 0$ (weighted)

	Controls		Treated	
	mean	sd	mean	sd
Utilization				
Visits at Regular GP	1.429	2.359	1.437	2.291
Total Visits	2.547	3.561	2.550	3.504
GP Visits	1.481	2.427	1.484	2.367
Specialist Visits	0.673	1.680	0.672	1.718
Ophthalmologist Visits	0.143	0.621	0.145	0.627
OB-GYN Visits	0.086	0.448	0.086	0.438
Psychiatrist Visits	0.064	0.648	0.063	0.694
Dermatologist Visits	0.056	0.400	0.056	0.431
Otorhinolaryngology Visits	0.038	0.336	0.037	0.322
Hospital Outpatient Visits	0.393	1.233	0.393	1.205
UPC (Primary Care)	0.977	0.054	0.977	0.054
Hospitalization				
Inpatient Days	0.540	4.452	0.543	4.560
Hospitalization Rate	0.042	0.200	0.042	0.200
Costs (CHF)				
Total HCE	1,230.457	3,144.552	1,238.256	3,530.079
Ambulatory Costs	486.864	1,142.582	486.010	1,190.780
Visits Costs	236.526	457.671	235.918	509.702
Drug Costs	315.910	1,204.604	324.191	1,978.152
Hospital Outpatient Costs	145.560	887.435	145.519	910.144
Inpatient Costs	276.251	2,067.161	277.079	2,010.165
Patient Characteristics				
Age	58.545	18.232	58.619	18.102
Female (Share)	0.530		0.531	
German-Speaking (Share)	0.678		0.679	
Swiss Citizen (Share)	0.787		0.785	
Chronic Condition (Share)	0.458		0.451	
No. of PCGs	0.771		0.762	
Central Switzerland (Share)	0.172		0.170	
Espace Mittelland (Share)	0.345		0.346	
Northwestern Switzerland (Share)	0.098		0.097	
Eastern Switzerland (Share)	0.109		0.111	
Ticino (Share)	0.025		0.025	
Physician Density (8km)	0.747	0.579	0.738	0.410
Distance to Regular GP (km)	5.056	9.022	4.851	8.754
Health Plan Choice				
Basic Plan (Share)	0.445		0.450	
Medium Deductible (Share)	0.235		0.234	
High Deductible (Share)	0.162		0.162	
PPO Health Plan (Share)	0.277		0.274	
HMO Health Plan (Share)	0.014		0.011	
TelMed Health Plan (Share)	0.010		0.010	
Accident Coverage (Share)	0.637		0.638	
Physician Characteristics (Regular GP)				
Age	61.593	5.968	63.527	6.217
Female (Share)	0.075		0.073	
Patients		197,504		12,960

Notes: This table reports weighted quarterly means for the pre-treatment period of all patients in our baseline sample assigned to the control group and the treatment group. Treatment group status is determined by a discontinuity in care of the regular primary care provider. Time is measured in event time, relative to a practice closure. Means are calculated based on two years before the treatment event. All costs are measured in CHF. The base category for 'region' is Zurich (numbers not displayed). 'Basic Plan' is a health plan with the standard deductible (CHF 300) and the standard model (free provider choice). Deductible levels are grouped into three categories: Small (CHF 300, numbers not displayed), Medium (500, 1,000), High ($\geq 1,500$). The base category for 'health plan type' is Standard (numbers not displayed). Chronic conditions are measured by pharmaceutical cost groups (PCGs). UPC (primary care) measures the share of all primary care visits with the regular GP (usual provider continuity, UPC).

Table A.3: Descriptive Statistics: Prevalence of PCGs (shares), $t < 0$ (weighted)

	Controls	Treated
	mean	mean
Asthma, Respiratory Diseases	0.048	0.048
COPD	0.008	0.008
Epilepsy	0.011	0.012
Rheumatism, Rheumatoid Diseases	0.053	0.053
Cardiovascular Disease	0.050	0.048
Crohn's Disease, Ulcerative Colitis	0.006	0.005
Acid Reflux	0.135	0.131
Type 1 Diabetes (Mellitus)	0.007	0.007
Type 2 Diabetes (no Hypertension)	0.016	0.015
Type 2 Diabetes with Hypertension	0.055	0.054
High Cholesterol, Hypertension	0.107	0.107
Parkinson's Disease	0.008	0.009
Transplant	0.001	0.001
Malignant Tumor	0.021	0.022
HIV, AIDS	0.001	0.001
Kidney Disease (incl. end-state)	0.002	0.002
Glaucoma	0.046	0.046
Thyroid Disease	0.044	0.044
Osteoporosis	0.027	0.027
Migraine	0.008	0.008
Depression, Anxiety, OCD	0.093	0.091
Chronic Psychosis	0.008	0.007
Addiction (Alcohol, Heroin)	0.004	0.004
Alzheimer's	0.004	0.003
Neuropathic Pain	0.005	0.005
ADHD	0.001	0.001
Patients	197,504	12,960

Notes: This table reports weighted quarterly means for the pre-treatment period of all patients in our baseline sample assigned to the control group and the treatment group. Treatment group status is determined by a discontinuity in care of the regular primary care provider. Time is measured in event time, relative to a practice closure. Means are calculated based on two years before the treatment event. Chronic conditions are measured by pharmaceutical cost groups (PCGs).

Table A.4: Causal Effects on Selected Outcomes (Dynamic Model)

	Year 1			Year 2			Year 3		
	Est.	SE	in %	Est.	SE	in %	Est.	SE	in %
A. Utilization:									
GP Visits	−0.161 ***	(0.035)	−10.9%	−0.203 ***	(0.033)	−13.7%	−0.159 ***	(0.036)	−10.7%
Specialist Visits	0.082 ***	(0.022)	12.2%	0.065 ***	(0.015)	9.7%	0.060 ***	(0.016)	8.9%
Hospital Outpatient Visits	0.022 **	(0.011)	5.5%	0.011	(0.012)	2.9%	0.026 *	(0.014)	6.6%
Total Visits	−0.058	(0.039)	−2.3%	−0.127 ***	(0.044)	−5.0%	−0.073	(0.047)	−2.9%
Ophthalmologist Visits	0.004	(0.004)	2.5%	0.001	(0.005)	0.8%	0.012 **	(0.005)	8.3%
OB-GYN Visits	0.003	(0.003)	3.4%	0.003	(0.003)	3.3%	0.011 *	(0.006)	12.8%
Psychiatrist Visits	0.005	(0.006)	8.6%	0.001	(0.006)	2.1%	0.004	(0.008)	6.2%
Dermatologist Visits	0.005	(0.004)	9.6%	0.010 ***	(0.003)	17.1%	0.004	(0.003)	7.6%
Otorhinolaryngology Visits	0.001	(0.002)	3.7%	0.003	(0.003)	8.1%	−0.001	(0.002)	−1.7%
B. Hospitalization:									
Hospitalization Rate	0.001	(0.001)	3.4%	0.001	(0.002)	2.1%	0.002	(0.002)	5.6%
Inpatient Days	0.031	(0.034)	5.6%	0.024	(0.036)	4.4%	0.050	(0.044)	9.3%
C. Costs:									
Total HCE	17.354	(25.735)	1.4%	−6.859	(28.720)	−0.6%	54.825	(35.602)	4.4%
Ambulatory Costs	23.011 **	(10.526)	4.7%	−2.333	(12.737)	−0.5%	12.930	(13.536)	2.7%
Visits Costs	7.742	(5.281)	3.3%	−1.613	(6.319)	−0.7%	0.175	(6.557)	0.1%
Drug Costs	−8.352	(6.700)	−2.6%	3.577	(10.905)	1.1%	23.191	(14.436)	7.2%
Hospital Outpatient Costs	9.303	(7.985)	6.4%	−6.906	(8.252)	−4.7%	7.471	(9.132)	5.1%
Inpatient Costs	9.936	(17.404)	3.6%	−1.330	(15.949)	−0.5%	12.455	(16.798)	4.5%
HCE per Visit (GP/Specialist)	3.794 ***	(1.324)	5.8%	2.827 *	(1.514)	4.3%	4.614 ***	(1.678)	7.0%
HCE per Visit	4.612 ***	(1.702)	5.3%	2.899 *	(1.710)	3.3%	5.246 ***	(1.946)	6.0%
D. Health Plan Choice:									
PPO Health Plan	−0.009	(0.005)	−3.2%	−0.021 ***	(0.007)	−7.6%	−0.024 ***	(0.009)	−8.7%
HMO Health Plan	0.011 ***	(0.003)	101.2%	0.020 ***	(0.005)	188.6%	0.025 ***	(0.007)	231.1%
TelMed Health Plan	0.001	(0.001)	8.9%	0.002	(0.002)	19.5%	0.002	(0.003)	21.1%
Observations									4,065,938
Patients									210,464

Notes: This table shows weighted estimates of causal effects of practice closures on outcomes, i.e., the coefficients of the interaction between the treatment group and post-treatment periods. The model includes patient fixed effects and time effects. Data is measured in quarterly terms. Standard errors are clustered at the physician level.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.5: Causal Effects on Outcomes by Chronic Condition I

	No Chronic Condition				Chronic Condition			
	Est.	SE	in %	Baseline	Est.	SE	in %	Baseline
A. Utilization:								
GP Visits	-0.102^{***}	(0.025)	−11.3%	0.90	-0.249^{***}	(0.046)	−12.1%	2.06
Specialist Visits	0.029^{**}	(0.013)	6.9%	0.42	0.110^{***}	(0.024)	12.0%	0.92
Hospital Outpatient Visits	0.000	(0.009)	0.2%	0.21	0.038^{**}	(0.018)	6.7%	0.58
Total Visits	-0.073^{**}	(0.032)	−4.7%	1.54	-0.100^{*}	(0.059)	−2.8%	3.55
Ophthalmologist Visits	0.006	(0.004)	8.4%	0.07	0.004	(0.006)	2.0%	0.22
OB-GYN Visits	0.004	(0.004)	4.7%	0.09	0.006	(0.004)	7.7%	0.08
Psychiatrist Visits	−0.002	(0.006)	−9.6%	0.02	0.009	(0.008)	9.2%	0.10
Dermatologist Visits	0.005^{*}	(0.003)	10.5%	0.05	0.008^{**}	(0.004)	12.5%	0.06
Otorhinolaryngology Visits	0.003	(0.002)	12.8%	0.03	−0.001	(0.003)	−1.2%	0.05
B. Hospitalization:								
Hospitalization Rate	−0.000	(0.001)	−1.9%	0.02	0.003	(0.002)	5.5%	0.06
Inpatient Days	0.008	(0.022)	4.7%	0.17	0.061	(0.058)	6.6%	0.91
C. Costs:								
Total HCE	7.185	(24.157)	1.4%	524.43	33.506	(40.247)	1.7%	1,946.38
Ambulatory Costs	−4.141	(8.465)	−1.6%	264.61	26.887	(17.913)	3.8%	705.64
Visits Costs	−3.090	(4.664)	−2.2%	137.49	7.698	(8.064)	2.3%	333.56
Drug Costs	6.447	(13.965)	6.1%	106.02	3.689	(11.484)	0.7%	540.61
Hospital Outpatient Costs	−2.575	(4.621)	−3.9%	65.24	8.954	(13.669)	4.0%	225.15
Inpatient Costs	3.213	(10.230)	3.2%	101.53	10.519	(23.967)	2.3%	451.23
D. Health Plan Choice:								
PPO Health Plan	-0.022^{**}	(0.009)	−7.0%	0.31	-0.013^{**}	(0.006)	−5.5%	0.24
HMO Health Plan	0.020^{***}	(0.006)	140.5%	0.01	0.017^{***}	(0.004)	223.7%	0.01
TelMed Health Plan	0.003	(0.003)	19.9%	0.01	0.000	(0.001)	5.8%	0.01
Observations				2,131,963				1,933,975
Patients				109,468				100,996
Patients (Treated)				6,454				6,506

Notes: This table shows weighted estimates of causal effects of practice closures on outcomes, i.e., the coefficients of the interaction between the treatment group and post-treatment periods. The model includes patient fixed effects and time effects. Data is measured in quarterly terms. Standard errors are clustered at the physician level.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.6: Causal Effects on Outcomes by Chronic Condition II

	ACSC				Diabetes, Hypertension			
	Est.	SE	in %	Baseline	Est.	SE	in %	Baseline
A. Utilization:								
GP Visits	-0.288^{***}	(0.055)	−12.6%	2.28	-0.240^{***}	(0.056)	−10.9%	2.20
Specialist Visits	0.127^{***}	(0.032)	15.3%	0.83	0.140^{***}	(0.031)	17.1%	0.81
Hospital Outpatient Visits	0.067^{***}	(0.025)	12.4%	0.54	0.060^{**}	(0.029)	11.0%	0.55
Total Visits	−0.094	(0.073)	−2.6%	3.65	−0.040	(0.077)	−1.1%	3.57
Ophthalmologist Visits	0.006	(0.008)	2.9%	0.21	0.004	(0.010)	1.9%	0.22
OB-GYN Visits	0.007	(0.005)	12.4%	0.06	0.011	(0.006)	21.2%	0.05
Psychiatrist Visits	0.009	(0.008)	18.1%	0.05	0.008	(0.008)	18.7%	0.04
Dermatologist Visits	0.003	(0.005)	4.8%	0.06	0.006	(0.006)	11.0%	0.06
Otorhinolaryngology Visits	−0.002	(0.004)	−4.0%	0.05	0.001	(0.005)	3.3%	0.05
B. Hospitalization:								
Hospitalization Rate	0.003	(0.003)	3.9%	0.07	0.005	(0.003)	6.8%	0.07
Inpatient Days	0.058	(0.080)	5.9%	0.99	0.031	(0.076)	3.2%	0.96
C. Costs:								
Total HCE	67.064	(57.310)	3.2%	2,077.16	79.319	(67.079)	3.8%	2,109.38
Ambulatory Costs	43.154^{*}	(25.907)	6.1%	711.62	40.348	(30.492)	5.6%	726.23
Visits Costs	12.204	(10.271)	3.6%	335.77	16.352	(10.604)	4.9%	334.01
Drug Costs	13.409	(16.346)	2.3%	574.96	20.085	(19.117)	3.4%	594.90
Hospital Outpatient Costs	19.486	(21.278)	8.5%	228.14	12.954	(26.113)	5.3%	243.83
Inpatient Costs	5.240	(35.673)	1.0%	517.45	0.278	(38.349)	0.1%	532.47
D. Health Plan Choice:								
PPO Health Plan	−0.007	(0.007)	−3.1%	0.23	−0.006	(0.007)	−2.5%	0.23
HMO Health Plan	0.015^{***}	(0.004)	245.6%	0.01	0.016^{***}	(0.004)	331.1%	0.00
TelMed Health Plan	−0.001	(0.001)	−17.7%	0.01	−0.001	(0.001)	−15.5%	0.01
Observations				970,967				728,211
Patients				50,955				38,103
Patients (Treated)				3,515				2,659

Notes: This table shows weighted estimates of causal effects of practice closures on outcomes, i.e., the coefficients of the interaction between the treatment group and post-treatment periods. The model includes patient fixed effects and time effects. Data is measured in quarterly terms. Standard errors are clustered at the physician level.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.7: Causal Effects on Outcomes by Insurance Type

	PPO Health Plan				Other Health Plan			
	Est.	SE	in %	Baseline	Est.	SE	in %	Baseline
A. Utilization:								
GP Visits	-0.133^{***}	(0.038)	−9.9%	1.34	-0.193^{***}	(0.035)	−12.5%	1.55
Specialist Visits	0.076^{***}	(0.022)	13.7%	0.56	0.067^{***}	(0.017)	9.3%	0.72
Hospital Outpatient Visits	−0.001	(0.015)	−0.3%	0.35	0.028^{**}	(0.013)	6.7%	0.41
Total Visits	−0.058	(0.048)	−2.6%	2.24	-0.098^{**}	(0.044)	−3.7%	2.68
Ophthalmologist Visits	0.003	(0.007)	2.5%	0.14	0.006	(0.004)	4.1%	0.15
OB-GYN Visits	0.006	(0.006)	7.2%	0.09	0.005	(0.004)	5.7%	0.08
Psychiatrist Visits	0.008	(0.008)	23.3%	0.03	0.002	(0.007)	2.4%	0.08
Dermatologist Visits	0.009^{**}	(0.004)	20.9%	0.04	0.005^{*}	(0.003)	8.9%	0.06
Otorhinolaryngology Visits	0.006^{**}	(0.003)	22.9%	0.03	−0.001	(0.002)	−1.8%	0.04
B. Hospitalization:								
Hospitalization Rate	0.002	(0.002)	6.2%	0.03	0.001	(0.002)	2.8%	0.05
Inpatient Days	0.022	(0.037)	5.7%	0.38	0.039	(0.041)	6.4%	0.61
C. Costs:								
Total HCE	15.481	(36.241)	1.6%	953.96	21.956	(32.498)	1.6%	1,358.05
Ambulatory Costs	−6.722	(15.754)	−1.6%	422.92	18.848	(12.642)	3.7%	512.60
Visits Costs	3.383	(6.767)	1.7%	204.23	1.802	(6.032)	0.7%	249.27
Drug Costs	−4.518	(11.765)	−1.9%	243.31	9.121	(11.963)	2.5%	358.27
Hospital Outpatient Costs	−14.532	(11.898)	−11.1%	130.69	10.600	(8.939)	7.0%	151.77
Inpatient Costs	19.813	(19.135)	9.2%	215.34	1.300	(17.242)	0.4%	303.09
D. Health Plan Choice:								
PPO Health Plan	-0.051^{***}	(0.014)	−5.7%	0.91	−0.003	(0.007)	−36.5%	0.01
HMO Health Plan	0.040^{***}	(0.010)	5,105.4%	0.00	0.009^{**}	(0.004)	61.4%	0.02
TelMed Health Plan	0.002	(0.003)	216.8%	0.00	0.002	(0.002)	11.2%	0.01
Observations				1,185,803				2,880,135
Patients				61,381				149,083
Patients (Treated)				3,842				9,118

Notes: This table shows weighted estimates of causal effects of practice closures on outcomes, i.e., the coefficients of the interaction between the treatment group and post-treatment periods. The model includes patient fixed effects and time effects. Data is measured in quarterly terms. Standard errors are clustered at the physician level.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.8: Causal Effects on Outcomes by Age

	Below 65				Above 65			
	Est.	SE	in %	Baseline	Est.	SE	in %	Baseline
A. Utilization:								
GP Visits	-0.151^{***}	(0.031)	−13.1%	1.15	-0.212^{***}	(0.045)	−10.8%	1.96
Specialist Visits	0.064^{***}	(0.016)	11.3%	0.56	0.079^{***}	(0.029)	9.5%	0.83
Hospital Outpatient Visits	0.017	(0.011)	5.0%	0.34	0.022	(0.018)	4.7%	0.46
Total Visits	-0.070^{*}	(0.041)	−3.4%	2.06	-0.112^{**}	(0.055)	−3.4%	3.25
Ophthalmologist Visits	0.005^{*}	(0.003)	7.8%	0.06	0.006	(0.008)	2.1%	0.26
OB-GYN Visits	0.006	(0.005)	5.8%	0.11	0.004	(0.003)	7.0%	0.05
Psychiatrist Visits	0.002	(0.009)	1.9%	0.09	0.007^{*}	(0.004)	29.0%	0.02
Dermatologist Visits	0.008^{***}	(0.003)	17.6%	0.05	0.004	(0.004)	5.5%	0.07
Otorhinolaryngology Visits	0.002	(0.002)	5.5%	0.03	0.001	(0.003)	1.7%	0.05
B. Hospitalization:								
Hospitalization Rate	−0.000	(0.001)	−0.4%	0.03	0.004^{*}	(0.002)	6.3%	0.06
Inpatient Days	−0.008	(0.032)	−2.2%	0.36	0.092	(0.058)	11.4%	0.81
C. Costs:								
Total HCE	12.351	(27.610)	1.4%	858.36	25.652	(40.279)	1.4%	1,779.50
Ambulatory Costs	11.329	(12.008)	2.9%	386.57	10.367	(16.961)	1.7%	627.69
Visits Costs	3.798	(5.287)	2.0%	185.94	−0.336	(8.168)	−0.1%	307.12
Drug Costs	12.957	(12.985)	5.4%	239.73	−6.769	(11.715)	−1.5%	444.52
Hospital Outpatient Costs	2.644	(7.806)	2.4%	111.13	3.544	(13.079)	1.8%	194.51
Inpatient Costs	−11.674	(15.075)	−6.0%	194.02	31.888	(23.369)	8.1%	395.41
D. Health Plan Choice:								
PPO Health Plan	-0.023^{***}	(0.008)	−7.9%	0.30	−0.008	(0.007)	−3.4%	0.24
HMO Health Plan	0.018^{***}	(0.006)	136.6%	0.01	0.018^{***}	(0.004)	263.2%	0.01
TelMed Health Plan	0.003	(0.003)	21.1%	0.01	−0.000	(0.001)	−1.6%	0.00
Observations				2,615,959				1,449,979
Patients				134,073				76,391
Patients (Treated)				7,615				5,345

Notes: This table shows weighted estimates of causal effects of practice closures on outcomes, i.e., the coefficients of the interaction between the treatment group and post-treatment periods. The model includes patient fixed effects and time effects. Data is measured in quarterly terms. Standard errors are clustered at the physician level.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

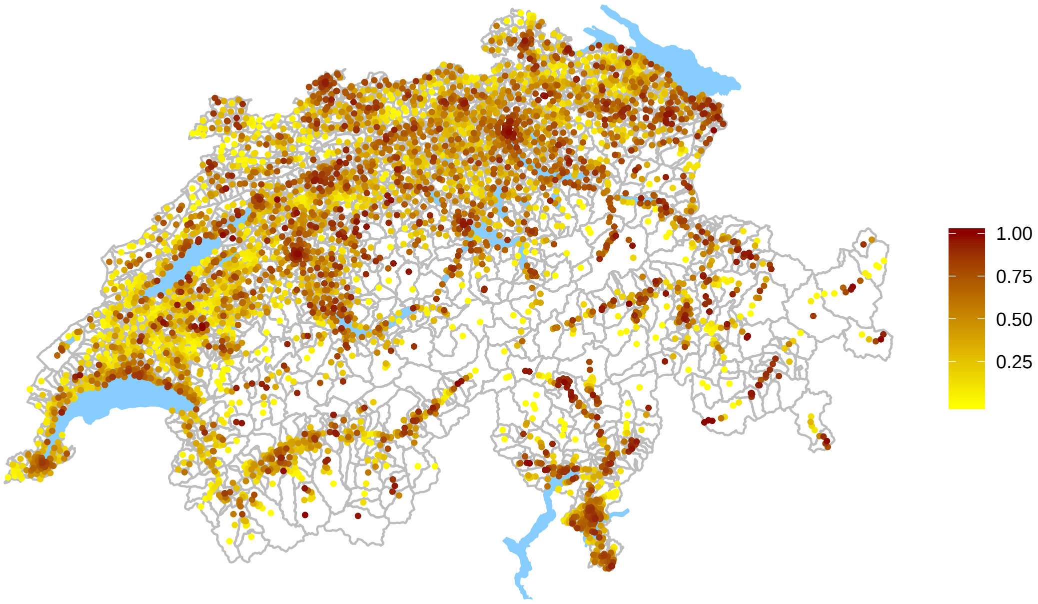
Table A.9: Causal Effects on Outcomes by Sex

	Male				Female			
	Est.	SE	in %	Baseline	Est.	SE	in %	Baseline
A. Utilization:								
GP Visits	-0.154^{***}	(0.033)	−10.9%	1.41	-0.194^{***}	(0.038)	−12.5%	1.55
Specialist Visits	0.075^{***}	(0.015)	13.3%	0.56	0.065^{***}	(0.022)	8.5%	0.77
Hospital Outpatient Visits	0.024	(0.016)	6.3%	0.37	0.016	(0.012)	3.8%	0.41
Total Visits	−0.056	(0.045)	−2.4%	2.35	-0.113^{**}	(0.048)	−4.1%	2.73
Ophthalmologist Visits	0.012^{***}	(0.004)	10.3%	0.12	−0.001	(0.006)	−0.5%	0.17
OB-GYN Visits	0.001	(0.001)	319.7%	0.00	0.009	(0.006)	5.5%	0.16
Psychiatrist Visits	0.003	(0.008)	4.4%	0.06	0.004	(0.007)	6.7%	0.07
Dermatologist Visits	0.004	(0.004)	6.9%	0.06	0.009^{***}	(0.003)	15.8%	0.06
Otorhinolaryngology Visits	0.002	(0.003)	5.9%	0.04	0.001	(0.003)	1.7%	0.04
B. Hospitalization:								
Hospitalization Rate	−0.000	(0.002)	−0.6%	0.04	0.003^{*}	(0.002)	7.6%	0.04
Inpatient Days	0.003	(0.044)	0.6%	0.54	0.062	(0.044)	11.3%	0.55
C. Costs:								
Total HCE	19.043	(38.251)	1.6%	1,205.36	20.907	(31.022)	1.6%	1,267.25
Ambulatory Costs	20.439	(15.598)	4.4%	462.90	3.180	(12.007)	0.6%	506.38
Visits Costs	6.004	(6.047)	2.8%	216.02	−1.026	(6.558)	−0.4%	253.46
Drug Costs	17.400	(17.573)	5.1%	339.63	−5.738	(7.483)	−1.8%	310.58
Hospital Outpatient Costs	9.255	(12.381)	6.1%	150.66	−2.219	(6.738)	−1.6%	140.98
Inpatient Costs	−16.318	(19.929)	−5.4%	301.25	27.254	(17.831)	10.7%	255.77
D. Health Plan Choice:								
PPO Health Plan	-0.020^{**}	(0.008)	−7.0%	0.28	-0.015^{**}	(0.007)	−5.7%	0.27
HMO Health Plan	0.017^{***}	(0.005)	151.5%	0.01	0.019^{***}	(0.005)	187.7%	0.01
TelMed Health Plan	0.002	(0.002)	19.4%	0.01	0.001	(0.002)	12.2%	0.01
Observations				1,808,839				2,257,099
Patients				93,689				116,775
Patients (Treated)				6,072				6,888

Notes: This table shows weighted estimates of causal effects of practice closures on outcomes, i.e., the coefficients of the interaction between the treatment group and post-treatment periods. The model includes patient fixed effects and time effects. Data is measured in quarterly terms. Standard errors are clustered at the physician level.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

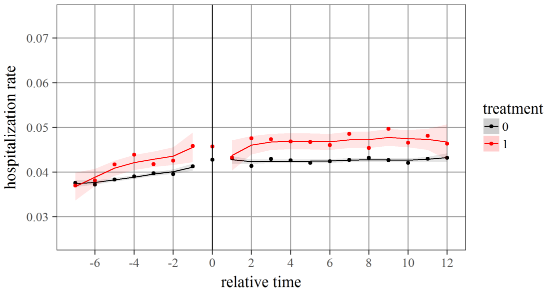
C.4 Additional Figures

Figure A.1: Geographic Variation in the Availability of Primary Care

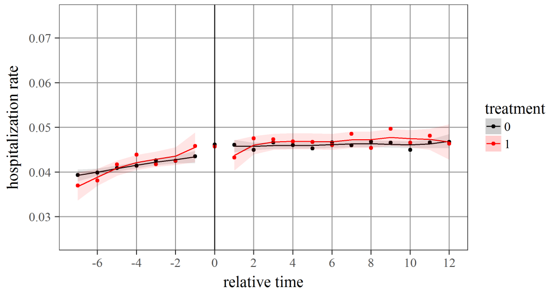


Notes: The figure displays the geographic variation in the primary care physician to population ratio for the year 2015. The measure is based on inverse distance weighting using a radius of 8 kilometers. Each dot represents a location defined by zip code and town name. For better readability, the scale corresponds to the empirical cumulative distribution function (CDF). The corresponding quartiles are: 25%: 0.32, 50%: 0.52, 75%: 0.76.

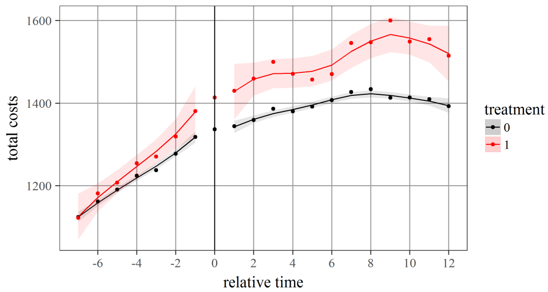
Figure A.2: Health-Related Outcomes: Hospitalization Rate and Total HCE



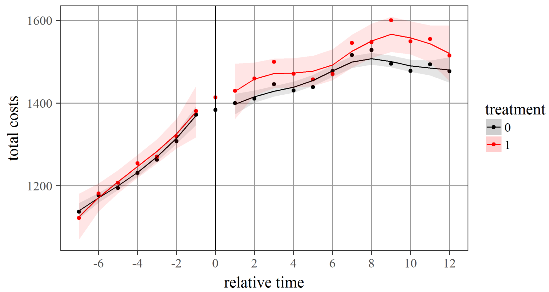
(a) Hospitalization Rate



(b) Hospitalization Rate, weighted



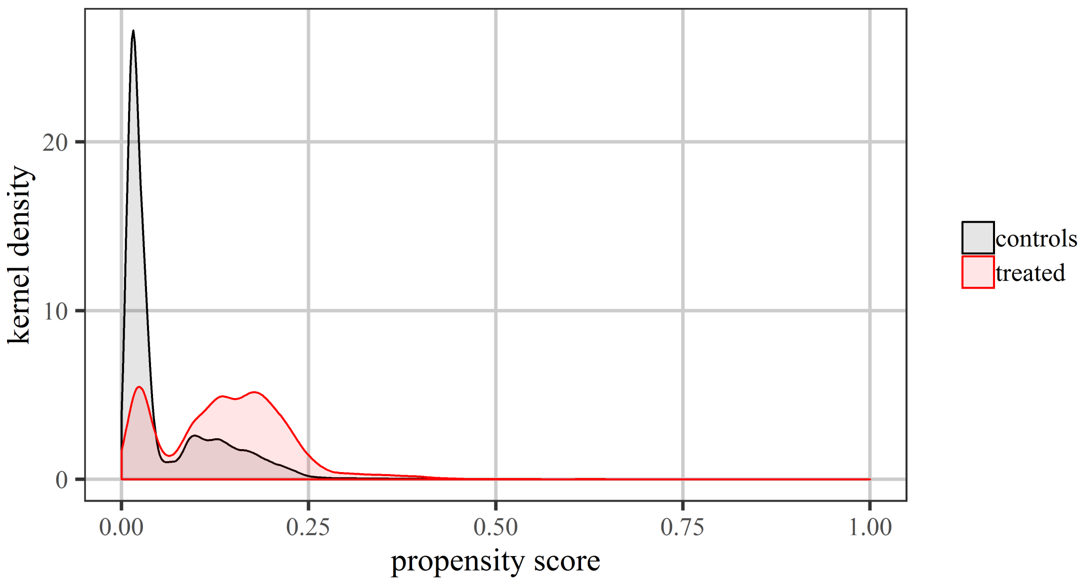
(c) Total Healthcare Expenditures (HCE)



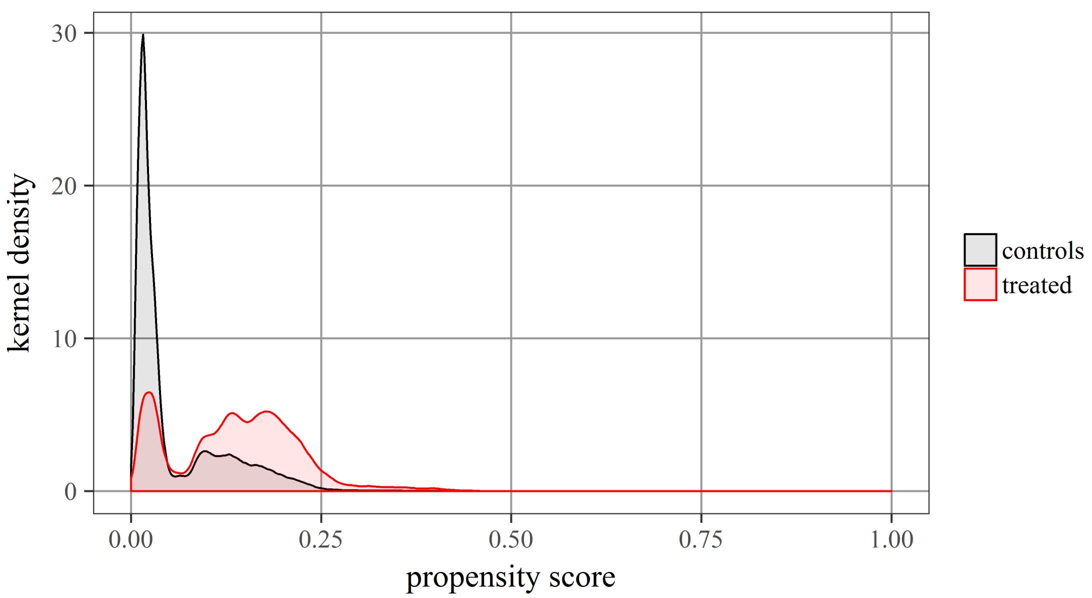
(d) Total HCE, weighted

Note: Dots correspond to quarterly averages (right panel: weighted quarterly averages) and the smoothed curve is based on a local linear regression using a triangular kernel and a bandwidth of 3. The shaded areas are 95%-confidence intervals. Event time indicates the quarter relative to the event of the practice closure (at $t = 0$).

Figure A.3: Kernel Densities of Estimated Propensity Scores



(a) full sample



(b) common support sample

Note: Kernel densities of estimated propensity scores.