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Do Financial Incentives Alter Physician Prescription Behavior?[*]

Evidence from Random Patient-GP Allocations

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Abstract

Do physicians respond to financial incentives? We address this question by analyzing the prescription behavior of physicians who are allowed to dispense drugs themselves through onsite pharmacies. Using administrative data comprising over 16 million drug prescriptions between 2008 and 2012 in Upper Austria, a naïve comparison of raw figures reveals that self-dispensing GPs induce 33.2% higher drug expenses than others. Our identification strategy rests on multiple pillars: First, we use an extensive array of covariates along with multi-dimensional fixed effects which account for patient and GP-level heterogeneity as well as sorting of GPs into onsite pharmacies. Second, we use a novel approach that allows us to restrict our sample to randomly allocated patient-GP matches which rules out endogenous sorting as well as principal-agent bargaining over prescriptions between patients and GPs. Contrary to our descriptive analysis, we find evidence that onsite pharmacies have a small negative effect on prescriptions. Although self-dispensing GPs seem to prescribe sligthly more expensive medication, this effect is absorbed by a much smaller likelihood to prescribe something in the first place, causing the overall effect to be negative.

JEL Classification: I11, I12
Keywords: Physician dispensing, drug expenses, physician agency, moral hazard

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I. Introduction

Ideally, physicians are perfect agents. They diagnose and provide treatments in a way patients would if they had perfect information. In reality, however, we observe profound variations in the provision of healthcare which cannot be explained by demand-side heterogeneities. Even after adjusting for prices and patient demographics, Gottlieb et al. (2010) for example document a $9,324 difference in per capita Medicare spending between Miami, FL and Salem, OR. In general, such regional variations may result either from demand-side differences in patient health and preferences, from supply-side heterogeneities such as physicians' education or preferences over treatments, or from geographical differences, for example air pollution.

Most of the observed variation in healthcare utilization can be attributed to the first channel. Using Austrian matched patient-GP data, Ahammer & Schober (2016) for example show that patient needs and preferences explain well over 90% of the variation in primary care expenses.[1] While the general practitioner (GP) explains only a small fraction (0.12%–4.36%) relative to the variation caused by patient-side heterogeneities and stochastic health shocks, they find that the most lenient 10% of GPs induce roughly 25% higher expenses than the average GP, which is a sizable portion. With healthcare expenditures rising across most countries, *"policy-makers are under pressure to control pharmaceutical expenditures without adversely affecting quality of care"* (Rashidian et al. 2015), so understanding sources of these variations is crucial for policy making.

In this paper we focus on one specific source of variation; namely financial incentives. Under specific conditions, physicians in Austria are allowed to dispense pharmaceuticals *themselves* in the form of onsite pharmacies, which makes them entrepreneurs and agents at the same time. Onsite pharmacies are permitted primarily for the purpose of ensuring unhindered access to medical drugs in rural areas where regular pharmacies are often difficult to reach. Operating an onsite pharmacy, however, allows physicians to earn a mark-up on every drug they prescribe. In medical situations where no clinical guidelines and consensus about treatments prevails, and where the marginal harm for the patient is small, there is a clear incentive to induce demand.[2]

Put differently, GPs may exploit their informational advantage to prescribe medication the patient's health status may not necessarily require, for the sole purpose of maximizing their own income. There is some causal evidence that doctors in fact do exhibit rent-seeking behavior (e.g., Melichar 2009 or Clemens & Gottlieb 2014, see section I.1), hence we hypothesize that having an onsite pharmacy leads, *ceteris paribus*, to an increase in drug expenses. In order to verify this conjecture, we use administrative data from the *Upper Austrian Sickness Fund* (UASF) which covers around 75% of the population in Upper Austria, one of nine provinces in Austria with roughly 1.4 million inhabitants as

[1] Ahammer & Schober (2016) perform variance decompositions based on components of hierarchical fixed effects models which contain patient-specific time-varying observables as well as both patient-level and GP-level fixed effects. Finkelstein et al. (2016) apply a similar methodology to U.S. data with geographical area as the second hierarchical level instead of GPs. They find that region-specific effects account for 54% of the total variation in Medicare utilization, while 47% can be explained by the patient.

[2] Medical situations in which clinical guidance is scarce, and the GP's benefits of supply-inducing are idiosyncratic to the patient, are coined *"gray area of medicine"* by Chandra, Cutler & Song (2012).

of 2016. We have access to a total of 23,820,854 observations representing the universe of GP consultations for these insurees. Contrary to our unconditional descriptive analysis which reveals that self-dispensing GPs induce on average 33.2% higher per patient drug expenses than others, first regressions reveal that doctors who run onsite pharmacies are in fact slightly *less* likely to prescribe medication in the first place, and induce roughly €2.1 ($2.25 or 5.9%) fewer drug expenses than their non-dispensing colleagues.

This is a surprising result, since the existing literature (Burkhard et al. 2015, Kaiser & Schmid 2016) in fact finds large positive effects of dispensing on drug prescriptions. Although our regressions so far control for physician ability and patient health status in a rigorous ways, and sorting of GPs into pharmacies can be conditioned on GP-level fixed effects, there are two other mechanisms we have to worry about: First, through a series of consultations patients and GPs may develop a principal-agent relationship which allows the patient to bargain over drug prescriptions. In this case, the onsite pharmacy coefficient may reflect the patient's prescription decision rather than the GP's, which is not what we want to measure. Second, patients may systematically avoid GPs who operate onsite pharmacies. If this type of endogenous sorting drives our results, we expect the pharmacy coefficient to be biased towards zero.

To avoid these issues, we suggest a novel identification approach which relies on a sample of randomly allocated patient-GP matches. In particular, we restrict our sample to drugs prescribed on weekends and public holidays. On weekends and public holidays, GPs in Austria rotate to provide out-of-hours services for the purpose of ensuring provision of basic healthcare, which is especially important in rural areas where no hospital is in close proximity. In case a patient decides to consult a physician outside opening hours, assignment can thus be considered random, because it depends only on the community's rotation schedule.[3] Using this strategy to account for endogenous sorting, our estimates become even larger in magnitude and retain their statistical significance. We interpret this as a sign of defensive medicine (Chandra et al. 2012, Lucas et al. 2010): *Ceteris paribus*, GPs seem more careful to induce demand in case they are not acquainted with the patient.

Overall, we find evidence that GPs who operate onsite pharmacies may not necessarily induce higher drug expenses than others. Although estimates suggest that GPs with onsite pharmacies prescribe slightly more expensive medication (but only if the GP is not acquainted with the patient, i.e., the patient-GP match is random), this effect is absorbed by a much smaller likelihood to prescribe something in the first place, causing the overall effect to be negative. This is not surprising: For our sample of UASF patients, we find that self-dispensing GPs earn on average an additional €109,882.5 ($118,328.65) in revenues per year, for doing the same work as non-dispensing GPs. Thus, the financial incentive to supply induce may not be as strong as initially thought, and dispensing GPs may even prescribe more defensively due to the additional income. However, why does the existing literature find evidence for supply-inducement then? First, Kaiser & Schmid

[3]To our knowledge, there is only one paper using a similar approach: Ahammer (2016) estimates labor market effects of supply-induced sick leaves. As a robustness check, he restricts his sample to sick leaves starting on weekends and public holidays as well. Since he does not observe the actual date of certification, however, Ahammer has to assume that it coincides with the start of the sick leave. In case they are systematically different, the allocation mechanism cannot be considered random anymore. In this paper, we decided to focus solely on drug prescriptions, since for those we know the exact date of consultation.

(2016) and Burkhard et al. (2015) may not sufficiently take into account sorting of GPs into onsite pharmacies, which would upward bias their estimated effect on drug expenses. Second, both studies use Swiss data where in certain cantons, *all* physicians are allowed to dispense drugs. In our setup, only country doctors are permitted to have onsite pharmacies. In rural areas, however, competition between GPs is low, and competition has been shown to be associated with more aggressive prescription behavior (Ahammer & Schober 2016, Léonard et al. 2009, Scott & Shiell 1997). Lastly, onsite pharmacies typically have a smaller variety of drugs than regular pharmacies (Pruckner & Schober 2016). For pharmaceuticals they do not have in stock, incentives to overprescribe are the same as for other GPs, which also contributes to zero effect.

I.1. Related literature and our contributions

Our paper generally belongs to the broad literature on practice styles and supply-induced demand (see, e.g., McGuire & Pauly 1991 and Chandra et al. 2012 for overviews). In particular, we contribute to the literature on the role of financial incentives in medical care. A recent example providing causal evidence is Clemens & Gottlieb (2014), who use price shocks triggered by regional Medicare consolidations in 1997 to estimate care elasticities with respect to reimbursement rates. They find that healthcare supplied to Medicare patients increases overproportionally with the reimbursement rate. Another notable example is Melichar (2009), who exploit within-physician variation in reimbursement schemes involving different financial incentives for marginal increases in the provision of healthcare. They find that GPs spend less time with patients they receive no marginal revenues for, as compared to patients whose expenses are reimbursed on a fee for service basis. There is also experimental evidence from the field: Kouides et al. (1998) for example document that physicians randomly selected to receive a monetary benefit for increasing their influenza immunization rate eventually achieved a 6.9 percentage points higher rate than physicians in the control group.

Related is also the literature on the role of onsite pharmacies in the choice of generic versus brand-name drugs in day to day medical care. In systems where physicians are allowed to prescribe and dispense drugs at the same time, Liu et al. (2009), Iizuka (2007, 2016), and Rischatsch et al. (2013) find that profit incentives significantly affect physician prescription behavior. Analyzing the interrelations between inpatient and outpatient prescription behavior, Pruckner & Schober (2016) find that GPs are less likely to adhere to the hospital's treatment choice if they dispense drugs themselves.

There is much less literature on the actual effect of physician self-dispensing on drug expenses. To our knowledge, there are currently only two studies which specifically consider that question: Kaiser & Schmid (2016) exploit geographical variation in dispensing regulations across Switzerland. They empirically match physicians from cantons where it is permitted to operate onsite pharmacies to physicians from cantons where it is prohibited. Using doubly robust estimation, Kaiser & Schmid find that physician dispensing increases medical drug expenditures by roughly 34% per patient.

Burkhard et al. (2015) replicate their analysis but decompose the estimated increase in expenditures into a price and a volume effect. They show that the volume effect is dominant, while the price effect is small and insignificantly different from zero. However, both papers implicitly assume that GPs sort exogenously into cantons where self-dispensing is permitted, and that patients are matched randomly to GPs, conditional on their explanatory variables. Although they use a very rich set of control variables, sorting based on unobservables cannot be fully ruled out.

We contribute to the literature in several important ways. First, we specifically take into account sorting of GPs into onsite pharmacies and endogenous matching between patients and GPs, the latter by employing a novel identification strategy allowing to draw a sample of randomly matched patient-GP pairs. Second, we introduce fixed effects estimation along with a rich set of covariates including a physician ability proxy based on adjusted mortality rates to the literature. Third, since we do not aggregate our data on the physician level, we can analyze the onsite pharmacy effect both on the extensive and on the intensive margin. Fourth, we are the first to analyze effect heterogeneities based on age, education, gender, and wages.

II. Institutional setting

Austria has a *Bismarckian* welfare system where virtually all residents have universal access to healthcare. Mandatory health insurance covers all medical expenses both in the inpatient and outpatient sector including prescription medicines.[4] The *Federation of Austrian Social Security Institutions*, an umbrella organization encompassing all 22 individual health insurance funds,[5] maintains a positive list of permitted pharmaceuticals, the so-called *Reimbursement Codex*. In 2010, the codex contained 4,200 different medications which patients have access to upon prescription by a physician and payment of a small prescription fee in the dispensing pharmacy.[6]

With 5 doctors per 1,000 inhabitants in 2013, Austria has the highest physician density among all OECD countries (OECD 2015). Outpatient care is mainly provided by around 19,000 independently practicing physicians of whom 56% are contracted with one or several health insurance funds. These contracted physicians (both GPs and specialists) can be accessed free of charge and without a referral, non-contracted physicians on the other hand charge a fee which will partly be reimbursed by the patient's insurance. Patients are not obliged to consult their GP before seeking specialist or inpatient treatment, thus general practitioners formally do *not* serve a gatekeeping function in Austria. Although it is still common to have a family doctor, patients may also switch GPs on a regular basis.

[4] According to Hofmarcher (2013), Austrian health policy follows the principle of ensuring equal access to health care for all, irrespective of demographic and socioeconomic preconditions. She states that, *de facto*, the health system comes very close to achieving this goal. Almost 99.9% of the population in 2011 was covered by health insurance, the quality of care is generally considered to be high, and most treatments and services are universally accessible. However, this comes at the expense of very high cost. Both in absolute terms and in percent of GDP, Austria ranks well above the EU-15 average in terms of health care expenditures (OECD 2015).

[5] Note that affiliation to one of these 22 health insurance funds may not be choosen freely but depends on occupation and place of residence of the patient. Thus there is no endogenous sorting into and no competition among health insurances.

[6] In 2012, the prescription fee was € 5.15 or $5.51 (Hofmarcher 2013). Pharmacies are reimbursed by the patient's health insurance for the prescribed drug's cost, which the fee is offset against.

For general practitioners, it is typically preferable to secure a contract with at least one health insurance fund, as it guarantees a constant influx of patients and has several bureaucratic advantages (ÖKZ 2007). Contracted positions, however, are limited. Both the geographical distribution as well the absolute number of contracted physicians is regulated by the *Federation of Austrian Social Security Institutions*. Medical professionals that strive for a GP position thus have to pass through an application procedure where candidates are selected based on professional aptitude. Only contracted physicians are allowed to maintain onsite pharmacies.

II.1. Country doctors and onsite pharmacies

In a country where almost half of the population lives in predominantly rural regions (Eurostat 2013), an important pillar of outpatient medical care are country doctors (in German called *"Landärzte"*). Officially, a country doctor is a contracted physicians who either practices in a community with up to 3,000 inhabitants, or is one of at most two contracted physicians in a single community (Austrian Medical Chamber 2013). According to the medical chamber, roughly 40 percent of general practitioners in Austria fall within this category. In 2013, this amounts to 1,563 doctors being responsible for over 43% of the population.

More than half of these doctors, however, are expected to retire within the next ten years. This poses an important challenge for officials and policy makers, who have long been lamenting about the lack of young doctors applying for vacant insurance contracts in rural areas (Austrian Medical Chamber 2013). Often living and working conditions discourage physicians to settle in these areas, the average number of applicants per country doctor vacancy in Upper Austria decreased from 5 in 2001 to 1.2 in 2012. Amongst other measures, onsite pharmacies are increasingly instrumentalized by policy makers to attract physicians and counteract the expected shortage of doctors in rural areas (Austrian Medical Chamber 2013).

Onsite pharmacies require physicians to act as entrepreneurs. Typically they purchase a selection of common medications from pharmaceutical wholesalers which they dispense directly to the patient upon issuing a prescription. Since prices are fixed through the insurance's reimbursement rate, onsite pharmacies cannot compete on prices with regular pharmacies. A country doctor is permitted to operate an onsite pharmacy if (1) she is contracted with at least one health insurance fund, (2) there is no regular pharmacy in her community, and (3) the next regular pharmacy is more than six kilometers away. In 2016, the government passed a law which allows GPs to keep their onsite pharmacy even when a regular pharmacy opens within their community, as long as the pharmacy is more than four kilometers away. In case a pharmacy opens within a radius of four kilometers around the physician's practice, operating an onsite pharmacy is no longer permitted.

II.2. Weekend prescriptions

General practitioners in Upper Austria typically work Monday to Friday. On weekends and public holidays, each community has a rotation schedule of GPs providing out-of-hours services in order to ensure the provision of basic health care. This institution is especially important in rural areas, where the next hospital is difficult to reach. In some communities, the rotation schedule is posted on a website or in local newspapers, in others, patients have to call the emergency ambulance (typically the Red Cross) where the dispatcher informs them about the GP on duty. In case a patient decides to consult a GP on a weekend or public holiday, assignment is therefore random since it depends solely on the community's rotation schedule.

As discussed in section IV, our main estimations are based on a sample restricted to prescriptions filed on weekends or public holidays. Indeed, this sample may be selected in case (1) patients postpone their consultation until after the weekend because their medical condition does not require urgent treatment, or (2) they choose to go to a hospital instead. As long as patients do not base their decision on whether the GP on duty has an onsite pharmacy, neither of these selection mechanisms biases our results. In order to avoid learning effects, we use only the first match between patient and GP, so typically the patient will not have much information about the doctor.

III. Data

The main source of data for our empirical analysis is the *Upper Austrian Sickness Fund* (UASF), which gathers detailed information on health care utilization in both the inpatient and outpatient sector for roughly one million insurees. As described in section II, these insurees correspond to about three quarters of the Upper Austrian population, composed of private as well as public sector workers, retirees, and unemployed people. We augment the data with information on patient education and wages from the *Austrian Social Security Database* (Zweimüller et al. 2009) as well as additional demographic information on physicians from the *Upper Austrian Medical Chamber*.

For our analysis we draw a sample comprising the universe of medical drug prescriptions issued by general practitioners between 2008 and 2012.[7] In total, we observe 16,341,428 prescriptions issued by 632 GPs to 1,135,893 patients — on average, this amounts to roughly 14 prescriptions per patient over the entire period. Additionally, we add all available consultations that did not result in a drug prescription to our data, which allows us to analyze the effect of financial incentives at the extensive margin, i.e., the overall probability of receiving medication when a GP is consulted. Our primary criterion for including a prescription is whether it is issued by a general practitioner, for self-dispensing GPs we also include drugs that are dispensed at a regular pharmacy (i.e., not sold at the onsite pharmacy).[8] In total, this leaves us with a sample of 23,820,854 consultations.

[7]Unfortunately, our data does not allow us to analyze outcomes other than medical drug prescriptions, since we do not have an exact date of consultation (which we need to define our weekend sample) for non-drug health services. Kaiser & Schmid (2016) find that drug and non-drug expenditures are complementary goods for self-dispensing physicians.

[8]This could, for example, be the case for certain uncommon medications (such as cancer drugs) the GP may not have in stock at his onsite pharmacy. In general, we expect onsite pharmacies to have a smaller variety of medications than regular pharmacies, which is also a result in Pruckner & Schober (2016).

Table 1 — Descriptive statistics.

	Full sample		Weekend sample[a]		Diff.[b]	Changers[c]	
	Mean	Std. dev.	Mean	Std. dev.		Mean	Std. dev.
Outcomes							
Positive expenses	0.686	0.464	0.541	0.498	0.145	0.688	0.463
Total expenses (in EUR)	35.642	147.779	24.191	156.145	11.451	35.963	201.439
Units of medication	2.010	3.899	1.362	3.046	0.648	1.967	3.804
GP characteristics							
On-site pharmacy	0.299	0.458	0.347	0.476	−0.048	0.746	0.435
Female	0.122	0.327	0.111	0.314	0.011	0.539	0.498
Age							
Under 35	0.002	0.039	0.001	0.035	0.0003	0	0
35 to 40	0.010	0.102	0.009	0.094	0.001	0.079	0.270
40 to 45	0.041	0.197	0.032	0.176	0.009	0.243	0.429
45 to 50	0.107	0.309	0.088	0.283	0.019	0.311	0.463
50 to 55	0.256	0.436	0.233	0.423	0.023	0.212	0.409
55 to 60	0.342	0.474	0.360	0.480	−0.018	0.138	0.345
60 to 65	0.201	0.401	0.227	0.419	−0.026	0.017	0.128
Over 65	0.042	0.200	0.051	0.219	−0.009	0	0
Adjusted mortality	1.000	0.003	1.000	0.003	0.0001	1.000	0.003
Patient characteristics							
Female	0.564	0.496	0.536	0.499	0.029	0.571	0.495
Age							
Under 20	0.098	0.297	0.141	0.348	−0.043	0.119	0.324
20 to 30	0.076	0.265	0.099	0.299	−0.024	0.076	0.265
30 to 40	0.087	0.281	0.109	0.312	−0.023	0.088	0.284
40 to 50	0.130	0.336	0.155	0.362	−0.026	0.127	0.333
50 to 60	0.159	0.366	0.167	0.373	−0.008	0.155	0.362
60 to 70	0.183	0.387	0.144	0.351	0.039	0.177	0.382
70 to 80	0.162	0.368	0.116	0.320	0.046	0.167	0.373
Over 80	0.106	0.308	0.069	0.253	0.038	0.091	0.287
Education							
Compulsory	0.063	0.243	0.073	0.260	−0.010	0.061	0.240
Apprenticeship	0.156	0.363	0.198	0.399	−0.042	0.162	0.368
High school	0.117	0.322	0.152	0.359	−0.034	0.118	0.323
University	0.034	0.182	0.040	0.196	−0.006	0.030	0.170
Missing	0.629	0.483	0.537	0.499	0.092	0.629	0.483
Daily wage (in EUR)	27.872	43.745	36.373	46.925	−8.501	27.393	42.628
Migrant	0.166	0.372	0.160	0.366	0.006	0.168	0.374
Medication history[d]	159.829	494.278	122.481	448.909	37.349	154.987	457.232
Hospital history[e]	0.599	3.812	0.463	3.303	0.136	0.562	3.599
ATC medication code							
Missing	0.033	0.178	0.039	0.194	−0.006	0.025	0.155
Alimentary tract and metabolism	0.108	0.310	0.079	0.270	0.029	0.115	0.319
Blood and blood forming organs	0.015	0.122	0.010	0.101	0.005	0.016	0.125
Cardiovascular system	0.199	0.399	0.136	0.342	0.063	0.206	0.405
Dermatologicals	0.015	0.120	0.012	0.111	0.002	0.014	0.116
Genito-urinary system	0.016	0.124	0.010	0.102	0.005	0.017	0.129
Systemic hormonal preparations	0.018	0.131	0.014	0.119	0.003	0.018	0.132
Antiinfectives for systemic use	0.059	0.236	0.067	0.250	−0.008	0.066	0.249
Antineoplastic and imm. agents	0.006	0.078	0.005	0.069	0.001	0.007	0.083
Musculo-skeletal system	0.065	0.247	0.051	0.220	0.014	0.066	0.248
Nervous system	0.102	0.302	0.073	0.261	0.028	0.088	0.283
Antiparasitic products	0.0004	0.020	0.0003	0.018	0.0001	0.0004	0.021
Respiratory system	0.044	0.205	0.038	0.190	0.006	0.041	0.198
Sensory organs	0.006	0.079	0.005	0.070	0.001	0.008	0.089
Various	0.001	0.028	0.001	0.026	0.0001	0.001	0.035
Sample size	23,820,854		2,089,438		—	484,415	

Notes: This table presents summary statistics for our sample of consultations.
[a] Sample is restricted to medications prescribed on weekends or public holidays.
[b] Difference in means between the full sample and the weekend sample.
[c] Sample of patients who receive medication from GPs that change their onsite pharmacy status at least once between 2008 and 2012.
[d] Medication history is the aggregate amount of drug expenses one year prior to the consultation.
[e] Hospital history is the aggregate number of days spent in hospital one year prior to the consultation.

Our main regressions are based on a subset of these data, namely drug prescriptions issued on weekends or public holidays (for convenience we may call this the 'weekend sample' henceforth). In case a patient was at the same GP multiple times on weekends or holidays, we keep only the first consultation in order to avoid learning effects. For reasons discussed in section IV.2, we are primarily interested in weekend and holiday prescriptions because they provide more reliable estimates than the full sample. Thus, we do not include drug prescriptions by specialists, since they typically do not provide out-of-hours services on weekends.

Summary statistics are provided in Table 1, where we provide first and second moments of our most important variables for the full sample, the weekend subsample, and a sample of 'changers'. The latter is simply a subset of the full sample comprising the largest connected set of consultations filed by GPs who open or close an onsite pharmacy at least once during our observation period. Because we include GP fixed effects in our estimations, these are in fact the observations which ultimately identify our results. Note that the means of the changer sample are remarkably similar to those obtained from the full sample, thus fixed effects estimates should be representative as well.

Our four outcome variables are discussed extensively in section IV. At the extensive margin, we estimate the effect of onsite pharmacies on a binary variable indicating whether at least one unit of medication is prescribed during the consultation (i.e., drug expenses are positive), and overall drug expenses of the consultation, including also zeros for consultations where no drug was prescribed. At the intensive margin, we look at drug expenses per unit and at the number of units prescribed, both conditional on receiving at least one unit of medication. On weekends and public holidays, in general it seems that slightly less medication is prescribed.

Our treatment indicator is a binary variable indicating whether the consulted GP operates an onsite pharmacy, and zero else. Around 30% of all GPs operate an onsite pharmacy, this corresponds roughly to the official numbers cited in section II.1. In the weekend sample, the fraction of GPs with onsite pharmacies is higher, which makes sense given that weekend consultations are used more by people living in rural areas, where also onsite pharmacies are much more common than in densely populated areas. For the GP, we also have information on gender and age: It seems that GPs in Upper Austria are predominantly men aged 50 or older. Again, these numbers coincide with the official figures presented in section II.1.

At the patient level, we control for age, wages, and health proxies — these are time-varying variables, and their means reflect mostly what we expect *a priori*. Additionally, we have information on gender, education, and migratory status. Overall, patients are more likely to be male, around 50% are between 50 and 80 years of age, and their highest educational degree is most likely apprenticeship training. Our health proxies are the sum of drug expenses in the year prior to the consultation ('medication history') and the aggregate number of days spent in hospital the year prior to the consultation ('hospital history'). On top of that, we include a full set of region-specific controls in our estimations.[9] These are especially important because we want to pick up as much location-specific hetero-

[9]We build geographical clusters based on the first three out of four figures of the patient's zip code — these correspond roughly to larger communities.

geneity as possible.

Finally, we use the *Anatomical Therapeutic Chemical* (ATC) classification system to control for the type of medication prescribed. Unfortunately, we do not have information on diagnoses, thus the ATC code serves as a proxy for the medical condition the patient suffers from. Around 40% of all drugs prescribed fall within one of those categories: 'Alimentary tract and metabolism' (e.g., laxatives, antidiarrhoeals, antidiabetics, vitamins, or dietary minerals), 'cardiovascular system' (e.g., beta blockers, cardiac stimulants, or antiarrhythmics), or 'nervous system' (e.g., analgesics, antidepressants, anti-ADHD agents, etc.) with cardiac therapy drugs being the most common one.

IV. Methodology

We estimate the following fixed effects model:

$$y_{ijt} = \vartheta \cdot \mathbf{1}\{osp_{ijt}\} + X_{ijt}\beta' + W_{it}\gamma' + Z_{jt}\delta' + M_i\varphi' + \eta_j + \tau_t + \varepsilon_{ijt} \tag{1}$$

where y_{ijt} is medical care received by individual $i = 1, \ldots, N$ provided by GP $j = 1, \ldots, J$ at time $t = 1, \ldots, T_i$, thus subscript ijt uniquely identifies a consultation. The treatment indicator $\mathbf{1}\{osp_{ijt}\} \in \{0, 1\}$ equals unity if GP j providing medical care to individual i maintains an onsite pharmacy at time t, and zero otherwise — our main coefficient of interest is therefore ϑ.

Additionally, the vector X_{ijt} contains consultation-specific control variables such as the first letter of the prescribed drug's *Anatomical Therapeutic Chemical* (ATC) classification system code, the vector W_{it} comprises time-variant patient-level controls such as age, wage, and a full set of community fixed effects, Z_{jt} captures time-variant GP-level control variables such as age and a measure of physician ability (adjusted GP-specific mortality rates, see section IV.2 for a detailed description), and M_i contains patient-level time-invariant control variables (e.g., gender, migratory status, and education). Finally, we include a full set of GP-level fixed effects η_j as well as year and month fixed effects τ_t.

IV.1. Outcome variables

Let exp_{ijt} be the sum of prices of all drugs prescribed in consultation ijt in Euros, and let vol_{ijt} be the number of units of drugs prescribed (typically packages). Then, our vector of outcome variables y_{ijt} consists of

(1) *"positive expenses"* $\mathbf{1}\{exp_{ijt} > 0\} \in \{0, 1\}$, an indicator variable which equals unity when patient i receives some medication from GP j during the consultation at time t, and zero if the patient does not receive any medication,

(2) *"total expenses"* $\log(1 + exp_{ijt})$, a continuous measure for the sum of the prices of all drugs prescribed during consultation ijt,

(3) *"expenses per unit"* $\log[1 + (exp_{ijt}/vol_{ijt})]$ is a continuous measure of drug expenses per unit prescribed during consultation ijt, conditional on $\mathbf{1}\{exp_{ijt} > 0\} = 1$, and

(4) *"medication volume"* vol_{ijt} is a discrete measure of the number of units prescribed during consultation ijt, conditional on $\mathbf{1}\{exp_{ijt} > 0\} = 1$,

where (1) can be interpreted as the extensive margin (i.e., the probability of receiving a drug in the first place), whereas (3) and (4) can be interpreted as the intensive margin (i.e., the price and volume effect conditional on receiving medication). Outcome (2) is also located at the extensive margin since it includes zeros as well (when no medication is prescribed).

Since most of our outcome variables are non-binary, we decide to model y_{ijt} as a linear additive function of the treatment indicator $\mathbf{1}\{osp_{ijt}\}$ and the set of control variables $(X_{ijt}, W_{it}, Z_{jt}, M_i, \eta_j, \tau_t)$. The coefficient of interest ϑ can then be interpreted as the difference in outcomes between self-dispensing and non-self-dispensing GPs. Because we include GP fixed effects η_j, we require osp_{ijt} to be time-variant for ϑ to be estimable. Thus, identification comes from GPs that open or close their onsite pharmacies during the observation period. As discussed in section II, the latter may for example be possible whenever a GP is not allowed to dispense drugs anymore because a regular pharmacy opens within a distance of four kilometers from her practice. In Table 1, we provide summary statistics for consultations of GPs changing their dispensing status; it turns out that their averages are remarkably close to those found for the full sample.

IV.2. Identification

In order to discuss identification of our main parameter ϑ, we use the potential outcomes framework (Rubin 1974). Consider again the model in equation (1). To simplify notation, define $d_k \equiv d_{k(ijt)} \equiv \mathbf{1}\{osp_{ijt}\}$, with $k(ijt)$ denoting consultation k of GP j to patient i at time t. Let y_{1k} be the potential outcome if physician j owns an onsite pharmacy at time t (i.e., if $d_k = 1$), and let y_{0k} the potential outcome if the physician does not dispense drugs herself ($d_k = 0$). Furthermore, let V_k denote the set of control variables in model (IV), $V_k = (X_{ijt}, W_{it}, Z_{jt}, M_i, \eta_j, \tau_t)$. Then, the conditional average treatment effect (ATE) we are ultimately interested in can be written as

$$\vartheta = \mathrm{E}[y_{1k} - y_{0k} \,|\, V_k]. \tag{2}$$

For ϑ in (2) to be identified, we require the treatment status d_k to be as good as randomly assigned, conditional on our set of covariates V_k. Formally,

$$\{y_{1k}, y_{0k}\} \perp\!\!\!\perp d_k \,|\, V_k, \tag{3}$$

where $\perp\!\!\!\perp$ denotes statistical independence. If the conditional independence assumption in (3) holds, the difference in conditional average outcomes has a causal interpretation. That is,

$$\mathrm{E}[y_{1k} - y_{0k} \,|\, V_k] = \mathrm{E}[y_k \,|\, V_k, d_k = 1] - \mathrm{E}[y_k \,|\, V_k, d_k = 0]. \tag{4}$$

Due to the extensive array of control variables, we are confident that most systematic differences in patients and GPs which may be correlated with d_k are accounted for in our regressions. However, there are two main threats to identification which we will discuss in more detail here, both related to self-selection. First, GPs may self-select into onsite pharmacies. Our main remedy to deal with that issue is to include GP fixed effects in model (1), arguing that the unobserved propensity to self-select into dispensing is likely a time-invariant personality trait, or at least a characteristic that does not change over time. Additionally, we follow Biørn & Godager (2010) and Markussen et al. (2012) and construct adjusted mortality rates as a proxy for physician ability, which is likely also a determinant of self-selection into dispensing and potentially time-variant (e.g., through further education). We proceed as follows: First, define a family doctor j for every patient i in the UASF data, and build a yearly panel for $i = 1, \dots, N$ and $t = 1, \dots, T$. Second, perform the following regression:

$$\Pr[\mathbf{1}\{dead_{it}\} = 1] = \pi_1 \cdot age_{it} + \pi_2 \cdot \mathbf{1}\{female_i\} + C_{it}\psi' + \xi_{it} \tag{5}$$

where $\mathbf{1}\{dead_{it}\} \in \{0, 1\}$ is a binary variable indicating whether patient i died in year t and C_{it} is a vector of community dummies. Third, average the predicted values obtained from estimating model (5) via OLS over all patients of GP j: Let $\mathfrak{P}_j$ be the set of patients of GP j, and let P_j be the cardinality of $\mathfrak{P}_j$, then

$$\Lambda_j = \frac{1}{P_j T} \sum_{i=1 \,|\, i \in \mathfrak{P}_j}^{P_j} \sum_{t=1}^{T} \Pr[\mathbf{1}\widehat{\{dead_{it}\}}] \tag{6}$$

is the adjusted mortality rate for GP j.

Controlling for physician ability along with age and GP-level fixed effects, we believe that most unobserved factors determining endogenous sorting of GPs into self-dispensing are accounted for in our model. A different sorting mechanism, however, may also impede identification, namely endogenous matching of patients to certain GPs. Again, we suppose that most factors driving these sorting decisions are already controlled for in our regressions (most importantly physician ability) — however, our results may still be biased in case there are unobserved determinants we do not catch. Therefore, we restrict our sample to consultations on weekends and public holidays.

On weekends and public holidays, GP practices in Upper Austria are typically closed. As discussed in section II.2, however, each community has a schedule of GPs rotating to provide out-of-hours services in order to ensure medical care in emergency cases. Since patients do not know which GP is on duty in case they get sick on a weekend, the allocation between patient and GP is as good as random. In section II.2, we briefly discussed two cases where this sample may still be selected on unobservables: (1) if the patient postpones her visit until after the weekend, and (2) if the patient decides to go to a hospital instead. As long as the patient does not base her decision on whether the GP on duty operates an onsite pharmacy, these cases will not affect identification in our framework.[10] Since the patient does not have any information about the GP on duty (which we ensure by keeping only the first patient-GP match in case there are multiple), we believe that this is a plausible assumption.

Another appealing feature of using only weekend prescriptions is that it eliminates certain principal-agent dynamics which may have evolved between patient and GP. Through

[10]Note that, even if the patient considers dispensing status of the matched GP in her decision whether to consult the GP or postpone her visit or go to a hospital, our estimates would be lower bounds of the actual effect.

TABLE 2 — Average per patient per year drug expenses for GPs with and without onsite pharmacies.

	On-site pharmacy		
	No (1)	Yes (2)	Difference (3)
Non-adjusted drug expenses (in EUR)	50.75	67.62	33.2%
Adjusted drug expenses (in EUR)	16.57	18.65	12.6%

Notes: This table gives the difference in average per patient per year drug expenses of GPs who do not maintain an onsite pharmacy ("No") and those who do ("Yes"). The adjusted difference is based on residuals from regressing drug expenses on a third-order polynomial in age and a female dummy.

a series of consultations, patients may develop a relationship with their GPs which allows them to bargain over drug prescriptions. Because we only use random patient-GP matches, such dynamics do not distort identification either. In section V, we report results both for the full sample as well as for the weekend sample since comparing these estimates may provide insight about effects of patient and GP side self-selection on drug prescriptions. Generally, we expect estimated onsite pharmacy effects to be upwards biased in case there is endogenous sorting of GPs into onsite pharmacies, and to be downwards biased in case patients systematically avoid GPs with onsite pharmacies.

V. RESULTS

In Table 2 we present average yearly per patient drug expenses, both for GPs operating an onsite pharmacy and for those who do not dispense drugs themselves. For non-dispensing GPs, non-adjusted drug expenses are based on prescriptions issued by the GP and dispensed at a regular pharmacy. For self-dispensing GPs, in contrast, we consider only prescriptions that are dispensed directly at the onsite pharmacy, disregarding drugs which are dispensed at a regular pharmacy.[11]

Average drug expenses of self-dispensing GPs are €16.87 ($18.17) or 33.2% higher than the drug expenses induced by other GPs. Since we only consider drugs dispensed and billed directly by the GP, €67.62 ($72.82) can be interpreted as the average yearly *revenue* generated through the onsite pharmacy. Self-dispensing GPs have on average 1,625 patients, their total average revenue per year is thus €109,882.5 ($118,328.63), which they earn on top of reimbursements paid by the health insurance for other medical services. The main purpose of this paper is to verify how much of this difference can be ascribed to the possibility of self-dispensing, and how much is caused by other factors such as patient health or endogenous sorting.

In Table 3, we take a closer look at the determinants of individual drug prescriptions.

[11] As discussed in section III, our data also comprises drugs prescribed by self-dispensing GP but dispensed by a regular pharmacy instead of the GP herself. The reason is that we are interested in how financial incentives affect prescription behavior overall, irrespective of whether the GP in fact sells the drug herself in the end or issues a prescription for a regular pharmacy.

Table 3 — Estimations results for full sample.

	Extensive margin		Intensive margin	
	Positive expenses (1)	Total expenses (2)	Expenses per unit (3)	Medication volume (4)
On-site pharmacy	−0.022***	−0.059**	0.011	0.014
	(0.008)	(0.028)	(0.009)	(0.021)
Patient is female	0.013***	−0.020***	−0.070***	0.014
	(0.001)	(0.004)	(0.002)	(0.010)
Patient drug history[a]	0.0001***	0.001***	0.0002***	0.001***
	(0.00001)	(0.0001)	(0.00002)	(0.0001)
Patient hospital history[b]	0.002***	0.019***	0.004***	0.061***
	(0.0001)	(0.001)	(0.0003)	(0.002)
Patient wage	−0.017***	−0.054***	0.016***	−0.055***
	(0.001)	(0.003)	(0.001)	(0.005)
Patient is migrant	0.023***	0.025***	−0.057***	0.009
	(0.002)	(0.006)	(0.004)	(0.011)
GP adjusted mortality	0.206*	0.665*	−0.141	2.332**
	(0.114)	(0.383)	(0.154)	(1.115)
GP fixed effects	Yes	Yes	Yes	Yes
Year and month	Yes	Yes	Yes	Yes
ATC codes	—	—	Yes	Yes
Patient education and age	Yes	Yes	Yes	Yes
GP age	Yes	Yes	Yes	Yes
Community fixed effects	Yes	Yes	Yes	Yes
Observations	23,820,854	23,820,854	16,341,428	16,341,428
Adjusted R^2	0.188	0.236	0.176	0.072

Notes: In this table we present results from estimating equation (1) on the full sample of general practitioner consultations. Every column represents an individual regression estimated by OLS: In column (1), the outcome is $\mathbf{1}\{exp_{ijt} > 0\}$; in column (2), the outcome is $\log(1 + exp_{ijt})$; in column (3), the outcome is $\log[1 + (exp_{ijt}/vol_{ijt})]$; and in column (4), the outcome is vol_{ijt}. Heteroskedasticity-robust and community-level clustered standard errors are given in parentheses below coefficients, stars indicate significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

[a] Medication history is the aggregate amount of drug expenses one year prior to the consultation.
[b] Hospital history is the aggregate number of days spent in hospital one year prior to the consultation.

Before we turn to our main analysis based on a sample of randomly allocated patient-GP matches, we run our estimations on the universe of drug prescriptions in order to gain a more comprehensive picture. For a detailed discussion of our four outcome variables we refer the reader to section IV.1 — in general, columns (1) and (2) should capture effects at the extensive margin (i.e., the overall probability of receiving medication), while columns (3) and (4) consider the intensive margin (i.e., given that the patient receives medication, what determines their expenses and volume). Inference is based on analytical heteroskedasticity-robust and community-level clustered standard errors.

In column (1) we consider the overall probability of receiving medication as an outcome. In contrast to our descriptive analysis, we find that consulting a GP who has an

TABLE 4 — Estimation results for sample of weekend and holiday prescriptions, extensive margin.

	Positive expenses			Total expenses		
	(1)	(2)	(3)	(4)	(5)	(6)
On-site pharmacy	−0.128***	−0.125***	−0.123***	−0.419**	−0.391**	−0.389**
	(0.049)	(0.046)	(0.045)	(0.192)	(0.175)	(0.175)
Patient is female		0.023***	0.022***		0.010**	0.009*
		(0.001)	(0.001)		(0.005)	(0.005)
Patient drug history[a]		0.0001***	0.0001***		0.001***	0.001***
		(0.00001)	(0.00001)		(0.0001)	(0.0001)
Patient hospital history[a]		0.002***	0.002***		0.016***	0.016***
		(0.0002)	(0.0002)		(0.001)	(0.001)
Patient wage		−0.020***	−0.020***		−0.050***	−0.050***
		(0.001)	(0.001)		(0.003)	(0.003)
Patient is migrant		0.007**	0.007**		−0.004	−0.004
		(0.003)	(0.003)		(0.010)	(0.010)
GP adjusted mortality			0.309			−0.937
			(0.642)			(2.022)
GP fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year and month	Yes	Yes	Yes	Yes	Yes	Yes
ATC codes	Yes	Yes	Yes	Yes	Yes	Yes
Patient education and age		Yes	Yes		Yes	Yes
GP age			Yes			Yes
Community fixed effects			Yes			Yes
Observations	2,089,438	2,089,438	2,089,438	1,130,723	1,130,723	1,130,723
Adjusted R^2	0.348	0.395	0.396	0.138	0.228	0.229

Notes: In this table we present results from estimating equation (1) on the sample of weekend and public holiday GP consultations. Every column represents an individual regression estimated by OLS: In columns (1), (2), and (3), the outcome is $\mathbf{1}\{exp_{ijt} > 0\}$; in columns (4), (5), and (6), the outcome is $\log(1 + exp_{ijt})$. Heteroskedasticity-robust and community-level clustered standard errors are given in parentheses below coefficients, stars indicate significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

[a] Medication history is the aggregate amount of drug expenses one year prior to the consultation.
[b] Hospital history is the aggregate number of days spent in hospital one year prior to the consultation.

onsite pharmacy in fact *decreases* the likelihood of receiving medication by 2.2 percentage points, which corresponds to 3.3% of the sample mean. In column (2), we find a similar effect: overall expenses decrease by 5.9% — in terms of the sample mean, this corresponds to a reduction from €35.64 ($38.38) to €33.54 ($36.12). Thus, we find rather small yet statistically significant effects at the extensive margin.

Columns (3) and (4) are only observed conditional on receiving at least one unit of medication. For both expenses per unit and the number of units we find small positive yet statistically insignificant effects. Thus, it seems that GPs with onsite pharmacies are slightly less likely to prescribe medication in the first place which leads also to a small decrease in overall expenses. Once medication is prescribed, we do not find any statistically significant differences between self-dispensing and non-self-dispensing GPs.

A priori, we would expect the onsite pharmacy effect to be positive. Similar to results

Table 5 — Estimation results for sample of weekend and holiday prescriptions, intensive margin.

	Expenses per unit			Medication volume		
	(1)	(2)	(3)	(4)	(5)	(6)
On-site pharmacy	0.031	0.038**	0.038**	0.033	0.032	0.044
	(0.019)	(0.019)	(0.019)	(0.125)	(0.113)	(0.118)
Patient is female		−0.074***	−0.074***		−0.072***	−0.070***
		(0.003)	(0.003)		(0.014)	(0.014)
Patient drug history[a]		0.0002***	0.0002***		0.001***	0.001***
		(0.00003)	(0.00003)		(0.0001)	(0.0001)
Patient hospital history[b]		0.003***	0.003***		0.052***	0.052***
		(0.0004)	(0.0004)		(0.003)	(0.003)
Patient wage		0.021***	0.021***		−0.048***	−0.047***
		(0.001)	(0.001)		(0.004)	(0.004)
Patient is migrant		−0.045***	−0.044***		−0.009	−0.014
		(0.004)	(0.004)		(0.013)	(0.013)
GP adjusted mortality			−0.102			−2.736
			(0.378)			(2.488)
GP fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year and month	Yes	Yes	Yes	Yes	Yes	Yes
ATC codes	Yes	Yes	Yes	Yes	Yes	Yes
Patient education and age		Yes	Yes		Yes	Yes
GP age			Yes			Yes
Community fixed effects			Yes			Yes
Observations	1,130,723	1,130,723	1,130,723	1,130,723	1,130,723	1,130,723
Adjusted R^2	0.166	0.215	0.217	0.019	0.066	0.066

Notes: In this table we present results from estimating equation (1) on the sample of weekend and public holiday GP consultations. Every column represents an individual regression estimated by OLS: In columns (1), (2), and (3), the outcome is $\mathbf{1}\{exp_{ijt} > 0\}$; in columns (4), (5), and (6), the outcome is $\log(1 + exp_{ijt})$. Heteroskedasticity-robust and community-level clustered standard errors are given in parentheses below coefficients, stars indicate significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

[a] Medication history is the aggregate amount of drug expenses one year prior to the consultation.
[b] Hospital history is the aggregate number of days spent in hospital one year prior to the consultation.

from the available empirical literature, also our descriptive analysis clearly points towards substantial excess prescription of dispensing GPs, which would be consistent with the notion of physicians simply being profit-maximizing individuals who respond to financial incentives. How can we rationalize this small negative effect? We do not necessarily neglect the possibility that GPs are profit-maximizing individuals, yet we conjecture that GPs may not necessarily face a strong enough incentive to overprescribe, because potential benefits do not exceed cost associated with the risk of harming the patient. Keep in mind that onsite pharmacies yield an average of € 109,882.5 ($118,328.63) in revenues for the same work other GPs earn nothing for. Thus, the additional income generated through onsite pharmacies may allow the GP to prescribe more defensively along the lines of Lucas et al. (2010). Furthermore, onsite pharmacies generally maintain a smaller variety of drugs, and for drugs they do not have in stock, dispensing GPs have the same incentives to induce demand than non-self-dispensing GPs. This could also explain a zero effect.

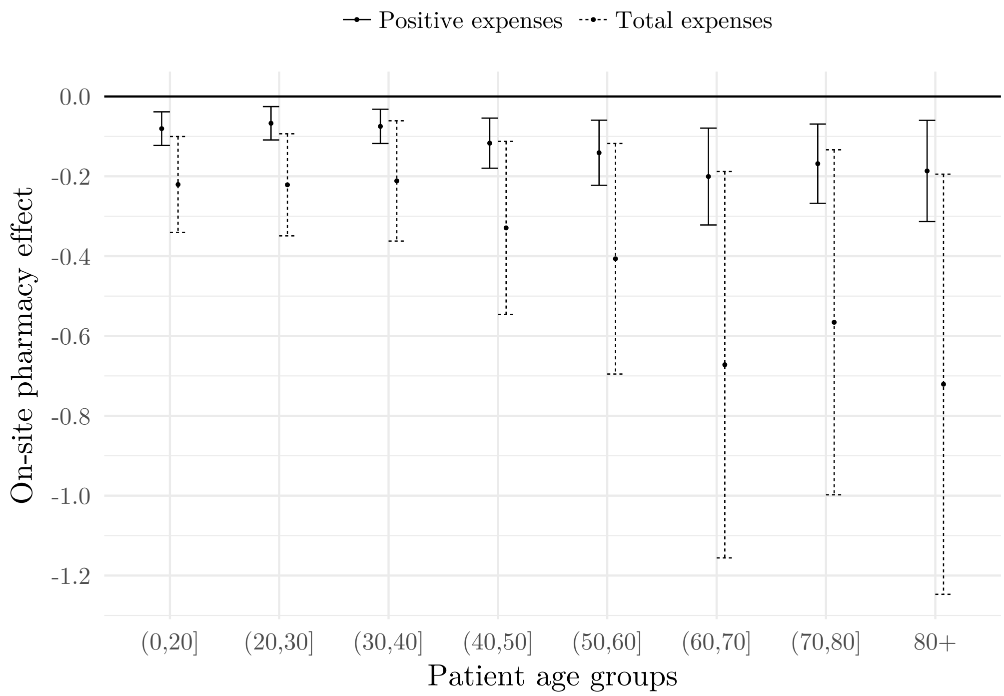
Why does the existing literature find signs of supply-inducement then? First, Kaiser & Schmid (2016) and Burkhard et al. (2015) both assume that sorting of GPs into onsite pharmacies is exogenous. This may cause an upwards bias to their results which we in turn pick up with our GP fixed-effects and the physician ability measure. Second, Kaiser & Schmid (2016) and Burkhard et al. (2015) both use Swiss data where in certain cantons *all* doctors are allowed to dispense drugs, whereas in Austria only country doctors are permitted to do so. Country doctors may differ from others in their propensity to induce demand, which could explain the diverging results. We also know that in rural areas competition between GPs is small, and competition is typically associated with more generous prescription behavior (Ahammer & Schober 2016, Léonard et al. 2009, Scott & Shiell 1997). A lack of competition may explain why our observed doctors induce lower drug expenses in general.

As discussed in section IV, we are worried that endogenous sorting between patients and GPs may partly drive the effects estimated on the full sample of GP consultations. We therefore turn to the sample of weekend and holiday prescriptions (see section IV.2 for details) where matches between patients and GPs are randomized. Estimation results can be found in Tables 4 and 5, where Table 4 considers effects at the extensive margin while Table 5 gives effects at the intensive margin. In both tables we present three different specifications for each outcome: In the first column we show the crude onsite pharmacy effect only controlling for GP fixed effects, time fixed effects, and the ATC code of the medical drug. In the second column we extend the set of covariates by patient-level observables — in particular, gender, age, migratory status, education, health proxies, and wages. In the third column we complete the model and also include time-varying GP level observables (i.e., age and our ability proxy) as well as community fixed effects.

On the extensive margin we still find a negative and statistically significant effect of consulting a self-dispensing GP on drug expenses. The probability of receiving medication in the first place decreases by at least 12.3 percentage points — this is a rather large effect, corresponding to a reduction from 54.1% to 41.8% in terms of the sample mean. Since, conversely, the likelihood of having zero medical expenses increases by 12.3 percentage points, also overall expenses decrease by a large 38.9%. This amounts to a reduction from €24.2 ($26.1) to €14.8 ($15.9). These results suggest that the negative effect of having an onsite pharmacy is much more pronounced outside opening hours when the patient-GP match is random. Potentially, this could be a sign of defensive medicine (Chandra et al. 2012, Lucas et al. 2010) in case GPs encounter patients whom they do not know, or conversely, of prescribing relatively more aggressive as soon as a relationship between principal and agent has been built and developed.

On the intensive margin (Table 5), we find a positive effect for drug expenses per unit: In case at least one unit of medication is prescribed, self-dispensing GPs induce 3.8% higher expenses per unit. Again, we do not find any effect again on medication volume. For patients that are unbeknownst to the GP, self-dispensing therefore reduces the likelihood of receiving medication. If medication is prescribed, however, it is marginally more expensive if the GP is self-dispensing. Siche this effect is offset by the smaller probability of prescribing something in the first place, the overall effect of onsite pharmacies on drug

Figure 1 — Heterogeneous effects for different patient age groups, weekend sample, extensive margin.



Notes: This graph depicts estimated onsite pharmacy coefficients and 95% confidence intervals from separate regressions where the sample is stratified on different patient age groups and the outcome variables are 'positive expenses' and 'total expenses' (see section IV.1 for a detailed description). The underlying sample consists of weekend and public holiday consultations.

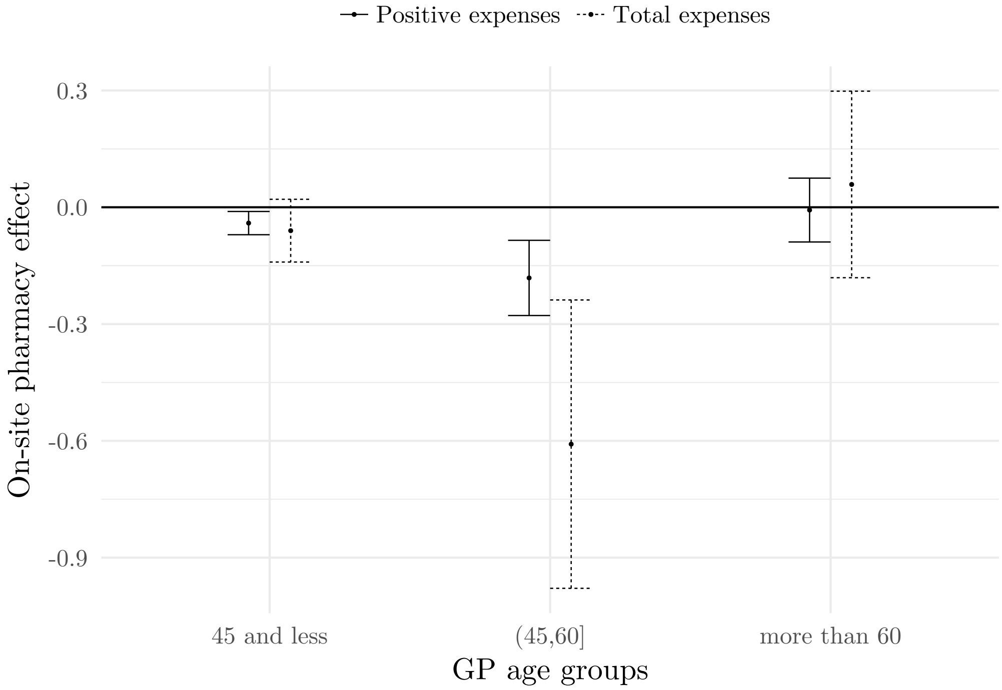
expenses is negative.

In terms of our other covariates, coefficients largely have their expected sign. Females are more likely to receive medication, yet at lower cost. Sicker patients (indicated through positive coefficients on the drug and hospital coefficients) receive more and relatively expensive drugs, migrants receive more but cheaper drugs, and low-ability GPs prescribe more, *ceteris paribus*. Interestingly, higher wages seem to have a negative effect on the extensive margin, which may also be a result of lower information asymmetry between principal and agent if we expect wages to be positively correlated with ability. Note also that our estimated onsite pharmacy coefficient is fairly stable across specifications, indicating a small correlation with other patient and GP-level observables.

V.1. Heterogeneous effects

In Figures 1, 2, and 3, we depict estimates of the onsite pharmacy coefficients for different subsamples of the population. We restrict our analysis to outcomes on the extensive margin in the weekend sample. In all estimations we use the most comprehensive specification from columns (3) and (6) in Table 4. Figure 1 suggests that the older the patient is, the more a GP who operates an onsite pharmacy is reluctant to prescribe medication. The patient-age gradient is nonlinear — while the magnitude of the effect for both measures

Figure 2 — Heterogeneous effects for different GP age groups, weekend sample, extensive margin.

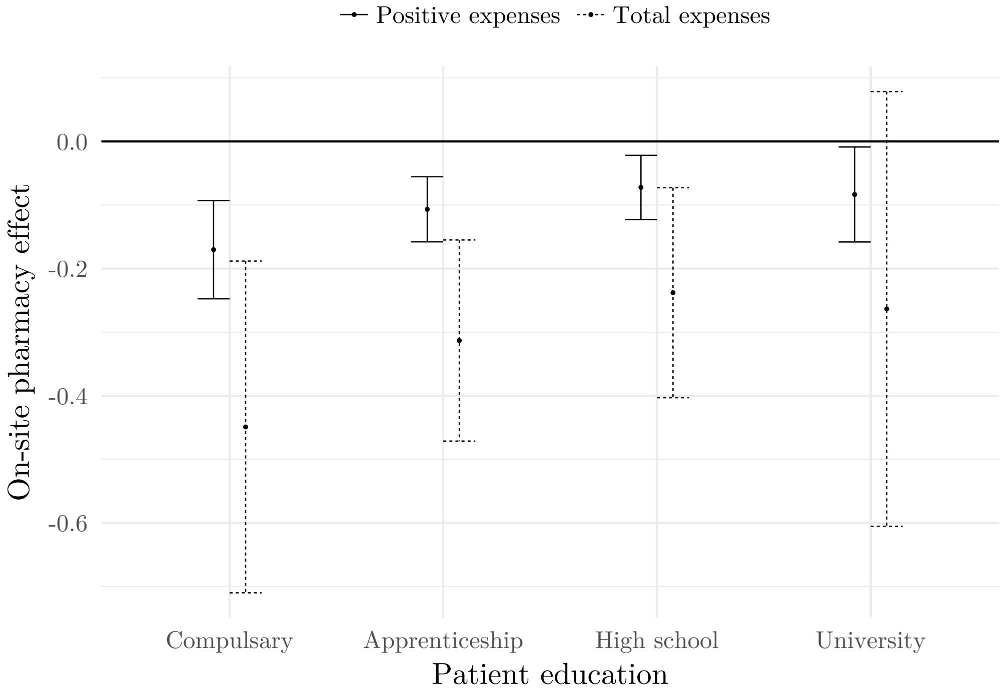


Notes: This graph depicts estimated onsite pharmacy coefficients and 95% confidence intervals from separate regressions where the sample is stratified on different GP age groups and the outcome variables are 'positive expenses' and 'total expenses' (see section IV.1 for a detailed description). The underlying sample consists of weekend and public holiday consultations.

of the extensive margin is fairly stable up to 40 years of age, the effect increases dramatically for subsequent age groups, until it again stabilizes at the 70 year mark. Figure 2 depicts effect heterogeneities for different GP age groups. We find that the negative effect on both outcomes at the extensive margin are mainly driven by mid-aged (45 to 60 years old) GPs, while both younger and older ones do not change their prescription behavior significantly if they have onsite pharmacies. For old GPs (above 60 years of age), we find a small positive effect, which is statistically insignificant nonetheless. Figure 3 shows that the onsite pharmacy effect increases with decreasing patient education, thus dispensing GPs prescribe more defensively when the patient is uneducated.

Finally, Table 6 presents heterogeneous results based on patient gender and wage (where high wage is defined as above median wage, and low wage is defined as below median wage) as well as GP gender for all four outcomes considered before. Interestingly, our estimated onsite pharmacy effects seem to be driven mostly by female doctors. For male doctors effects on the extensive margin are negative as well yet smaller in magnitude and statistically insignificant. We do, however, observe a positive and borderline significant effect on number of units prescribed for males. In terms of patient gender we find almost equal effects throughout, although they generally seem to be slightly stronger for females. In terms of patient wage, effects are stronger for those earning below median.

FIGURE 3 — Heterogeneous effects for different patient education groups, weekend sample, extensive margin.



Notes: This graph depicts estimated onsite pharmacy coefficients and 95% confidence intervals from separate regressions where the sample is stratified on different patient education groups and the outcome variables are 'positive expenses' and 'total expenses' (see section IV.1 for a detailed description). The underlying sample consists of weekend and public holiday consultations.

TABLE 6 — Heterogeneous effects, weekend sample

	Patient gender		Patient wage		GP gender	
	Male (1)	Female (2)	High (3)	Low (4)	Male (5)	Female (6)
Positive expenses	−0.112***	−0.132**	−0.092***	−0.130**	−0.021	−0.189***
	(0.037)	(0.052)	(0.024)	(0.052)	(0.017)	(0.046)
Total expenses	−0.367**	−0.405**	−0.290***	−0.411**	−0.015	−0.642***
	(0.147)	(0.199)	(0.080)	(0.205)	(0.044)	(0.187)
Expenses per unit	0.019	0.054***	−0.025	0.049***	0.039	0.030
	(0.028)	(0.017)	(0.039)	(0.019)	(0.030)	(0.024)
Medication volume	0.202*	−0.086	0.211***	−0.014	0.218*	−0.126
	(0.116)	(0.160)	(0.078)	(0.147)	(0.116)	(0.160)

Notes: In this table we present results from estimating equation (1) on different subsamples of the population, with only weekend and public holiday GP consultations considered. Every cell in the table represents an individual regression estimated by OLS. Heteroskedasticity-robust and community-level clustered standard errors are given in parentheses below coefficients, stars indicate significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

VI. Conclusions

Ideally, physicians are perfect agents. In reality, however, we observe striking differences in health care provision which cannot be explained by patient health or preferences. An important determinant of these differences are financial incentives. In this paper, we study whether physicians who are allowed dispense drugs themselves through onsite pharmacies show different prescription patterns than others. It turns out that, although they have much larger per patient drug expenses than other GPs, we find negative to no effects once we control for an extensive array of covariates and account for sorting of GPs into onsite pharmacies and matching between patients and GPs.

We have several explanations for this result which contrasts the existing literature. First, Kaiser & Schmid (2016) and Burkhard et al. (2015) both assume that sorting of GPs into onsite pharmacies is exogenous, which potentially causes their results to be upwards biased. In our framework, this type of sorting should be picked up by GP fixed-effects and a measure of physician ability. Second, Kaiser & Schmid (2016) and Burkhard et al. (2015) both use Swiss data where in certain cantons *all* doctors are allowed to dispense drugs, whereas in Austria only country doctors are permitted to do so. Country doctors may differ from others in their propensity to induce demand, and a lack of competition decreases incentives for overprescription behavior. Note, however, that we do not necessarily neglect the possibility that GPs are profit-maximizing individuals, yet the financial incentives to overprescribe may not be strong enough in our case if potential benefits do not exceed cost associated with the risk of harming the patient. Onsite pharmacies yield an average of € 109,882.5 ($118,328.63) in revenues for the same work other GPs earn nothing for. Thus, the additional income generated through onsite pharmacies may allow the GP to prescribe more defensively. Finally, note that GPs with onsite pharmacies generally maintain a smaller variety of drugs, and for drugs they do not have in stock, dispensing GPs have the same incentives to induce demand than non-self-dispensing GPs, which could also explain a zero effect.

The target of future research clearly should be to obtain further evidence on the relationship between onsite pharmacies and prescription behavior for other countries. Also, our empirical set-up does not allow us to look at outcomes other than drug prescriptions; analyzing effects on non-drug services along the lines of Kaiser & Schmid (2016) would definitely add to our understanding of onsite pharmacies.

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