



# Financial incentives and antibiotic prescribing patterns: Evidence from dispensing physicians in a public healthcare system

Barbara Stacherl<sup>a,b,\*</sup>, Anna-Theresa Renner<sup>c,d</sup>, Daniela Weber<sup>e,f</sup>

<sup>a</sup> Health Economics and Health Policy Research Group, Institute for Advanced Studies Vienna (IHS), Josefstädter Straße 39, 1080, Vienna, Austria

<sup>b</sup> Socio-Economic Panel, German Institute for Economic Research (DIW Berlin), Mohrenstraße 58, 10117, Berlin, Germany

<sup>c</sup> Department of Public Finance and Infrastructure Policy at the Institute of Spatial Planning, TU Wien, Karlsplatz 11, 1040, Vienna, Austria

<sup>d</sup> Weatherhead Center for International Affairs, Harvard University, 1737 Cambridge Street, Cambridge, MA, 02138, USA

<sup>e</sup> Health Economics and Policy Division, Vienna University of Economics and Business, Welthandelsplatz 1, 1020, Vienna, Austria

<sup>f</sup> International Institute for Applied Systems Analysis (IIASA), Wittgenstein Centre for Demography and Global Human Capital (IIASA, OeAW, Univ. Vienna), Schlossplatz 1, 2361, Laxenburg, Austria

## ARTICLE INFO

Handling Editor: R Smith

### Keywords:

On-site pharmacy  
Prescribing variation  
Antibiotic dispensing  
Physician behavior  
General practice  
Administrative data  
Austria

## ABSTRACT

To ensure sufficient access to healthcare in remote areas, some countries allow physicians to directly dispense prescribed drugs through on-site pharmacies. Depending on the medication prescribed, this may pose a significant financial incentive for physicians to over-prescribe. This study, therefore, explored the effect of on-site pharmacies on antibiotic dispensing in a social health insurance system. Investigating physicians' prescribing behavior is especially relevant in the case of antibiotics, as over-utilization expedites antimicrobial resistance, leading to the development of untreatable bacterial infections. The empirical analysis was based on comprehensive administrative data on 13,741 antibiotic prescriptions issued by all 4044 public general practitioners (GPs) in Austria between 2016 and 2019. Switches from dispensing to non-dispensing status (and vice versa) were exploited in a difference-in-difference framework to mitigate a potential selection bias. GPs with the right to dispense over the entire observed period were used as the control group, and those who had either lost or gained the right to dispense as the treatment group. The results from a log-linear mixed model show that not currently operating an on-site pharmacy is associated with a 9.2% lower dispensing rate (i.e., antibiotics per 1000 yearly consultations). The results are robust to potential differences between GPs who switch from dispensing to non-dispensing and those who switch from non-dispensing to dispensing, to potential patient sorting, and to different functional forms. A prescribing effect interpretation (i.e., financial incentives give rise to more prescriptions for antibiotics) explains the observed volume effect provided that the share of unfilled antibiotic prescriptions issued by non-dispensing physicians does not exceed 4%.

## 1. Introduction

Adequate access to healthcare, a key goal of health policy (WHO, 2000), includes the provision of sufficient financial and geographic accessibility to medication for everybody in need. To make prescription drugs accessible to all patients, irrespective of place of residence, countries such as Austria, the Netherlands, and Switzerland allow (to a certain extent) direct physician dispensing, thus integrating the roles of prescribing and dispensing. While this is convenient for patients, concerns have been raised that the prescribing behavior of physicians could be affected by considerations of financial gain, as dispensing physicians can generate additional income by prescribing more generously than

necessary.

At the same time, over-prescribing of antibiotics is a public health concern, as it increases the probability of antimicrobial resistance in the population, which itself leads to an increased number of untreatable infectious diseases caused by bacteria (Llor and Bjerrum, 2014). This has been shown to increase morbidity and mortality rates in people infected with resistant strains, which eventually results in higher healthcare costs (see Elbasha, 2003, for examples). Despite medical guidelines on antibiotic prescribing being available, antibiotics are frequently prescribed for non-antibiotic-appropriate diagnoses (Björkman et al., 2013; Brabers et al., 2018; Nowakowska et al., 2019). For many medical conditions, more consultations are leading to an antibiotic prescription than is

\* Corresponding author. Socio-Economic Panel, German Institute for Economic Research (DIW Berlin), Mohrenstraße 58, 10117, Berlin, Germany.

E-mail addresses: [bstacherl@diw.de](mailto:bstacherl@diw.de) (B. Stacherl), [anna-theresa.renner@tuwien.ac.at](mailto:anna-theresa.renner@tuwien.ac.at) (A.-T. Renner), [dweber@wu.ac.at](mailto:dweber@wu.ac.at) (D. Weber).

deemed appropriate by experts—this is frequently the case for respiratory tract indications which are often of viral origin, where antibiotic treatment has limited effectiveness (e.g., Dekker et al., 2015; Pouwels et al., 2018). In a recent discrete choice experiment, Sydenham et al. (2022) identified C-reactive protein (CRP) levels as particularly influential in GP antibiotic prescribing choices, suggesting a potential for reducing treatment uncertainty through CRP testing. Identifying the factors that determine prescribing behavior is thus key to avoiding over-utilization of antibiotics, and hence, welfare loss due to antimicrobial resistance.

Financial incentives as potential co-determinants of medical decision-making have been discussed extensively within the literature on demand inducement (for overviews see e.g., Chandra et al., 2011; McGuire, 2000). It is suggested that income-motivated inducement is more likely when the “correct” medical decision is not entirely clear (Hillman, 1990) and when marginal harm for patients is small (Chandra et al., 2011, p. 403). Arguably, antibiotic (over-)prescribing is characterized by low immediate patient harm and some treatment uncertainty (see above). In the context of physician dispensing, GPs act as both an agent of the patient and an entrepreneur. It can thus be argued that the prescribing behavior of physicians with an on-site pharmacy (OSP) could be impacted by the financial incentives posed by the OSP.

Financial incentives as determinants of prescribing behavior have been studied by investigating effects of physician dispensing regimes on drug expenditure (e.g., Bodnar et al., 2021; Chou, 2003; Kaiser and Schmid, 2016). Studies also highlighted the main pathways via which expenditure effects could materialize, namely substitution effects such as changes in prescription size, price, or type (e.g., Iizuka, 2012; Müller et al., 2022; Rischatsch et al., 2013) and volume effects, that is, changes in the number of items prescribed (e.g., Ahammer and Zilic, 2017; Burkhard et al., 2019; Iizuka, 2007).

Several studies on expenditure effects found physician dispensing to be related to higher per patient drug expenses (Baines et al., 1996; Bodnar et al., 2021; Chou, 2003; Kaiser and Schmid, 2016; Müller et al., 2022). Some showed that higher expenditures were driven, among other factors, by substituting a larger number of smaller packs (Bodnar et al., 2021; Müller et al., 2022). In the same vein, Rischatsch et al. (2013), Liu et al. (2009), and Iizuka (2012), found a substitution effect for Switzerland, Taiwan, and Japan of brand-name vs. generics, showing that dispensing physicians tend to prescribe a larger share of drugs that yield a higher markup. Ellegård et al. (2018) showed that substitution effects are also relevant for other types of financial incentive, reporting an increased share of narrow-spectrum antibiotics prescribed after the introduction of a pay-for-performance regime in Sweden which rewarded physicians financially for meeting certain prescribing targets.

Burkhard et al. (2019), investigating the relative importance of volume and substitution response for dispensing physicians in the Swiss context, found that higher drug expenditures were mainly driven by a volume effect, that is, dispensing rights resulted in a higher number of drugs being dispensed, but not necessarily more expensive drugs. Likewise for Switzerland, Filippini et al. (2014), taking advantage of regional differences in dispensing regimes, used a spatial econometric model to investigate antibiotic use. Controlling for demand, access, and spatial spillovers, their findings showed higher levels of antibiotic use in regions that allowed physician dispensing. For the English context, Baines et al. (1996) reported that higher drug expenditures for dispensing general practices were driven by more drug items dispensed overall. Park et al. (2005) analyzed the prescribing of antibiotics after a dispensing ban on Korean physicians. Including a quality dimension, they reported that antibiotic prescribing for viral illnesses declined substantially after the ban, while prescribing for bacterial illnesses saw only a minimal reduction. Iizuka (2007) examined the problem of agency of dispensing physicians in the Japanese healthcare context, concluding that dispensing physicians’ choice of prescription was sensitive to the markup incentive. While many studies on physician dispensing found a positive volume effect of on-site pharmacies (e.g., Baines et al., 1996;

Burkhard et al., 2019; Filippini et al., 2014; Iizuka, 2007; Park et al., 2005), Ahammer and Zilic (2017) found a negative effect on the number of drug prescriptions in Austria. Controlling both for GPs sorting into on-site pharmacies and patients sorting into GP practices, the authors found a much smaller likelihood of GPs in on-site pharmacies issuing a prescription. As well as the literature covering on-site pharmacy effects, some evidence exists on volume effects induced by another type of financial incentive. Martens et al. (2007) reported a small reduction in the number of antibiotic prescriptions issued after the introduction of a pay-for-performance premium in the Netherlands.

Looking at OSPs and volume effects in particular, studies to date focused on prescribing behavior (i.e., physician behavior). However, the number of drugs dispensed depends not only on the physician’s prescribing behavior, but also on the behavior of the patient in terms of redeeming the prescription. The redeeming behavior of patients is of relevance when comparing dispensing and non-dispensing physicians, as in the case of an OSP, prescriptions are typically filled immediately, while in the case of non-dispensing physicians, patients have to fill their prescription at a pharmacy later. Findings on shares of unfilled antibiotic prescriptions range from 1.7% in a Swedish study (Ekedahl and Månsson, 2004), to 4.6% in a U.S. study (Kennedy et al., 2020), to 14.3% in a Polish study (Kardas et al., 2019). To date, patient behavior potentially varying according to the dispensing status of the prescribing physician has not sufficiently been addressed in the literature on the dispensing effects of on-site pharmacies.

This paper aims to explore the effect of on-site pharmacies on antibiotic dispensing in a social health insurance system. In particular, we focus on the healthcare system in Austria which ensures health insurance coverage for practically all residents. Health insurance funds, which are not in competition with each other, cover inpatient and outpatient medical expenses, including visits to the doctor and prescription drugs. Most GPs in outpatient care (61%) are contracted with a social health insurance fund, meaning that their services are fully covered by health insurance, while patients can only claim partial reimbursement for services provided by non-contracted doctors. Outpatient physician services are mainly provided in solo practices, and patients can freely choose the provider without any formal gate-keeping system being in place. In our study, we make use of the fact that in the Austrian public healthcare system, GPs are allowed to operate an OSP where this is regarded necessary to ensure access to medication. Dispensing rights are issued to GPs practicing in (rural) areas where a public pharmacy is not readily accessible. This allows the GPs in question to earn a markup on every medication that they prescribe and dispense. Dispensing GPs thus might have a financial incentive to prescribe antibiotics (among other drugs) more generously. Thus, to study the role of financial incentives in antibiotic dispensing, this paper investigates the potential effects of on-site pharmacies (OSP) on antibiotic dispensing volumes associated with general practitioners (GPs).

We contribute to the literature by investigating the causal effect of on-site pharmacies on antibiotic dispensing volumes. We analyzed a rich physician-level panel dataset drawn from data on administrative pharmacy claims containing information on the volume of antibiotics dispensed per physician per year. The study population comprised all public outpatient GPs in Austria, some of whom have the right to dispense drugs on site. We also exploited the fact that some physicians changed their OSP status over time to investigate the effect of an OSP on antibiotic dispensing volumes. To elucidate causes of varying antibiotic dispensing volumes by OSP status, we distinguished between a prescribing effect (difference by OSP status in the number of antibiotics prescribed due to physicians’ prescribing behavior) and a dispensing effect (difference by OSP status in the number of antibiotics dispensed due to patients’ prescription-filling behavior).

## 2. Methodology

### 2.1. Institutional setting

In the Austrian healthcare system, antibiotics require a prescription issued by a certified physician to be dispensed in a pharmacy. Prescription medications are generally covered by the health insurance funds, but patients have to pay a small co-payment or “prescription fee” per item (set at €6.10 in 2019, the last year of analysis). If the price of the prescribed medication is below the prescription fee, patients pay the regular price without reimbursement. Dispensed drugs are registered so that claims can be settled between the pharmacy and the health insurance funds. Drugs below the threshold are thus only registered for patients exempt from medication co-payment. Patients are eligible for exemption from medication co-payment if their net income is below a defined threshold and automatically exempt if they have done co-payments amounting to 2% of their yearly net income.

To ensure access to medication in remote areas where pharmacies are hard to reach, Austrian GPs are allowed to dispense drugs on site under certain conditions. These are met if the respective GP has a contract with a health insurance fund, no public pharmacy is present in the municipality of the practice location, and there is no public pharmacy within 6 km (see §29 *Apothekengesetz* [Austrian Pharmacy Law]). It should be noted that a GP is entitled, but not obliged, to run an OSP. While the dispensing status is usually constant over time, switching from OSP to no OSP or vice versa can occur for three main reasons. (1) A public pharmacy opens within a 4-km radius of the practice location, so the respective GP loses the right to dispense (see §29 *Apothekengesetz* [Austrian Pharmacy Law]). According to the Austrian Chamber of Pharmacists, the number of public pharmacies has grown from 1352 in 2015 to 1404 in 2021. (2) GPs moving their practice from an ineligible (urban) to an eligible (rural) area could switch from no OSP to OSP, while GPs moving from eligible to non-eligible would have to give their OSP up. (3) When eligible, GPs may decide to open or close an OSP at any time.

The physician remuneration in Austria is based on a mix of fee-for-service and contact capitation paid by the insurance funds (Bachner et al., 2018, p. 107). With this remuneration system, GP income is not tied to the number of drugs prescribed; hence prescribing has no financial benefit. In the case of physician dispensing, however, there is an incentive to prescribe generously, as the dispensing GP earns a markup on every medication dispensed.

Importantly, patients do not face cost differences between public and on-site pharmacies. In either case, they pay a prescription fee only or the drug price (which is the same in public and on-site pharmacies) if that same is below the prescription fee threshold. Differences for patients amount largely to convenience – dispensing upon prescription at the OSP vs. redemption at public pharmacy after prescription, with availability of medications at public pharmacies generally having a broader assortment of drugs available.

### 2.2. Econometric specification

We estimated the GP prescribing propensity using a log-linear mixed model within a difference-in-differences framework. The logarithmized GP prescribing rate (number of antibiotic prescriptions per 1000 yearly consultations) was modeled as being dependent on whether a GP operates an OSP; hence, it exploits switches from being dispensing to non-dispensing, and vice versa.

Simply using a binary explanatory variable for whether a GP operates an OSP within the full sample would bias the results if dispensing GPs’ prescribing behavior differs systematically from that of non-dispensing GPs. There are two possible reasons why such a systematic difference could occur: (1) the differing healthcare demands of the patient populations; and (2) physician self-selection into an OSP. The former is a plausible concern, as self-dispensing physicians are, by

definition, practicing in rural regions where the patient population might differ significantly with respect to health status and, hence, medication needs. Additionally, patients might sort into self-dispensing physicians’ practices to meet personal prescription expectations. The second potential source of bias stems from the fact that GPs can choose where to practice and whether to operate an OSP (if they are legally permitted). Potentially, GPs willing to over-prescribe or those with a reluctance to be implicitly monitored by a nearby pharmacist, might self-select into practices where they can operate an OSP.

To combat these potential biases, we estimated our *main model* with a subsample consisting only of GPs who ever had an OSP, exploiting the fact that some of these GPs changed their dispensing status over the study period (possible reasons for status change are outlined in section 2.1.). We applied a difference-in-differences estimation to this reduced sample, where the GPs who operated an OSP throughout the entire period served as the control group, and the GPs with a change in their OSP status functioned as the treatment group. As our treatment and control group faced very similar institutional (no public pharmacy within reach), geographical (rural), and selection (opted to operate an OSP) settings in the untreated period, we are confident in the validity of difference-in-differences approach. Next to the *main model* we estimated two versions of a *base model*, which did not employ a difference-in-differences approach but simply included a dummy for an OSP in a given year. In *base model 1* the full sample containing all GPs was used, while in *base model 2*, like in the *main model*, the reduced sample was used but no distinction was made between treated and untreated physicians.

We used a two-dimensional panel with the population of GPs  $i = 1, \dots, N$  observed over the years 2016 to 2019. As not all GPs in the sample were observed over the entire period, the panel was unbalanced. As there was information at the district as well as physician level, the data were hierarchically structured with regional grouping of physicians. We estimated the following mixed model as our main regression:

$$\log(y_{ijt}) = \alpha + DID_{ijt} \varphi + TREAT_{ij} \theta + X_{ijt} \beta' + M_{ij} \gamma' + W_{jt} \delta' + T_t \eta' + p_{0i} + r_{0j} + e_{ijt}$$

where  $y_{ijt}$  is the annual prescribing rate of GP  $i = 1, \dots, N$  in district  $j = 1, \dots, J$  in year  $t = 1, \dots, T$ . The dummy variable *TREAT* controls for any unobserved differences between the treatment and control group, taking on a value of one if physician  $i$  changed OSP status during the observation period. Our main variable of interest, *DID*, is a binary variable taking on a value of one if physician  $i$  ever changed dispensing status and does *not* operate an OSP in year  $t$ , and zero otherwise. Hence, *DID* equals zero if GP  $i$  was a dispensing physician during the entire study period (for the control group), or during year  $t$  (for the treatment group). Note that the “treatment” in our study represents the change to *no* dispensing rights, as our control group consisted of GPs who always had dispensing rights and not those who never had those rights. We believe the former group to be more similar to the treatment group, who had dispensing rights for at least one year during the study period, and that it therefore allows a more credible identification of the causal effect. Further, it is worth mentioning that the treatment did not occur at the same time for all GPs and could work in both directions: some GPs in our panel started without an OSP in 2016 and gained the right to dispense on site throughout the following years, while others began by operating an OSP and stopped doing so later on. To account for general time trends affecting all GPs equally, we also included year dummies ( $T_t$ ).

The matrix  $X_{ijt}$  contains time-varying practice characteristics (e.g., yearly consultations, share of patients under 15),  $M_{ij}$  comprises time-invariant GP characteristics (gender and age group in 2016), and the matrix  $W_{jt}$  captures time-varying regional effects (e.g., degree of urbanization and GP density in practice location district). We included GP-level random effects  $p_{0i}$  – as observations by the same GP are likely more similar than observations by different GPs – and district-level random effects  $r_{0j}$  to capture random variability across districts.

We conducted several sensitivity analyses to check the robustness of our findings in three ways. Firstly, to support our choice of treatment and control groups, we considered potential differences between GPs who switched from dispensing to non-dispensing and those who switched from non-dispensing to dispensing (separate analyses for switching to and switching from) and potential patient sorting into dispensing GPs according to prescribing expectations (analysis including only patients 70 and older who were assumed to be less mobile and thus exhibit less sorting). Secondly, we conducted analyses with additional/modified demographic and socioeconomic variables. Thirdly, we employed fixed effects specifications instead of mixed modeling, and fourthly, we used different functional forms to account for model uncertainty.

Statistical analyses were carried out using the software R, version 4.0.2 (R Core Team, 2020). The package *dplyr* (Wickham et al., 2020) was used for data manipulation, *ggplot2* (Wickham, 2016) was used for visualization, and the *lme4* (Bates et al., 2015) was the modeling package used.

### 2.3. Simulation analysis

We conducted additional analyses simulating patient behavior to elucidate two potential causes of a volume effect for dispensing rates, namely physician prescribing behavior and patient prescription-redeeming behavior. Our data only allows for statements to be made on antibiotic prescriptions that were in fact filled, as prescriptions that patients chose not to fill are not recorded. Dispensing GPs usually dispense the medication at the time of issuing a prescription, while patients of non-dispensing GPs might reconsider whether to go to a pharmacy and fill the prescription after it has been issued. Therefore, we cannot determine whether an observed volume effect for the dispensing rate captures a prescribing effect (dispensing GPs issue more antibiotic prescriptions) or a dispensing effect (antibiotic prescriptions by dispensing GPs are more likely to be filled). A predominant prescribing effect would ascribe the observed higher dispensing volumes of dispensing GPs to increased antibiotic prescribing due to financial incentives, while a predominant dispensing effect would ascribe them to better primary adherence due to direct dispensation.

We investigated physician prescribing and patient redeeming as potential causes of a volume effect by simulating hypothetical patient behavior, explicitly modeling different average shares of unfilled prescriptions per GP. The literature reports varying shares of unfilled antibiotic prescriptions, ranging from 1.7% in a Swedish study (Ekedahl and Månsson, 2004), 4.6% in a U.S. study (Kennedy et al., 2020), to 14.3% in a Polish study (Kardas et al., 2019). Accounting for this uncertainty we looked at ten scenarios of the average share of unfilled prescriptions per GP ranging from 1% to 10%. To simulate these scenarios, we randomly dropped a share of the prescriptions issued by each dispensing GP corresponding to one of the scenarios. For each scenario, we estimated the *main model* 100 times with different randomly dropped prescriptions and report the share of models that yielded a significant negative effect.

### 2.4. Data sources

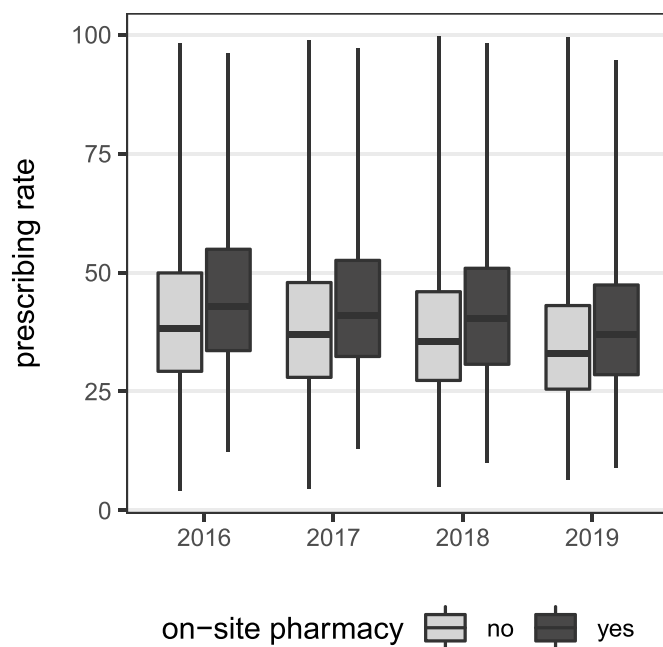
We exploited physician-level data on reimbursed antibiotic prescriptions provided by the Austrian Federation of Social Insurance (DVSV). This dataset was drawn from anonymized pharmacy claims including all antibiotic drugs (ATC J01) prescribed by a contracted GP and dispensed in a public pharmacy or an OSP between 2016 and 2019. In addition to the number of antibiotics prescribed per GP per year, we observed whether the GP currently (on December 31st of year *t*) operated an OSP, data on personal, patient population, and practice characteristics, as well as the district where the practice was located and the number of contracted GPs and specialists per district, which were also provided by the DVSV. At the district level, we calculated the GP and

specialist density as well as a population density indicator using publicly available registry data (Statistik Austria, 2020).

As the dataset was based on claims data of dispensed antibiotics, only GPs who issued at least one prescription that was subsequently filled in a pharmacy were included. Complete prescription data were only available above a certain price threshold, as patients are required to pay out-of-pocket costs up to the prescription fee threshold (not registered in claims data), and only some patients are exempt (registered in claims data). To avoid bias, only prescriptions for drugs priced above the prescription fee threshold in a respective year were considered. Only active GPs with solo practices were included—that is, those registered as contracted solo physicians at the beginning and the end of the year (in group practices: 517 observations of 193 GPs). Additionally, we excluded observations that were missing data on the number of patients per year (50 observations of 28 GPs), which might occur for non-practicing, self-prescribing GPs. Moreover, the cases of GPs holding contracts with different social insurance funds for different services (355 observations of 155 GPs) were excluded, as the numbers of registered consultations and of registered prescriptions do not refer to the same patient population for these GPs. This left us with a sample containing 13,741 observations of 4044 individual GPs. Our main regression was based on a subset of this data including only GPs who had ever had the right to operate an OSP in the period observed. Following the same exclusion criteria for this sample, 6 observations of 3 GPs were excluded due to missing patient data and 26 observations of 14 GPs were excluded due to the insurance fund criterion, leaving us with a sample containing 2793 observations by 799 individual physicians who had ever had an OSP. For convenience, we call this the *OSP sample* from here on.

### 2.5. Variables

The dependent variable of interest was the GP prescribing rate, defined as the number of antibiotics prescribed per 1000 yearly consultations. Fig. 1 shows the antibiotic prescribing rate for the years 2016–2019 for dispensing and non-dispensing GPs (using the full



**Fig. 1.** Prescribing rate 2016–2019 by on-site pharmacy status (full sample). Prescribing rate: number of antibiotic (ATC code J01) prescriptions per 1000 yearly consultations per general practitioner. On-site pharmacy status refers to current dispensing status of each respective year. Outliers with prescribing rate >100 ( $N = 80$ , 0.6%) not shown in graph for legibility. Source: Own calculations based on data from Austrian Federation of Social Insurances.



sample). The average prescribing rate was slightly higher for dispensing GPs in all observed years and decreased over time both for dispensing and non-dispensing GPs. Although not directly testable, the similar trend over time for dispensing and non-dispensing GPs offers support for the parallel trends assumption for our differences-in-differences estimation. Substantial variability in the prescribing rate was observed across physicians. In 2019, the 90th percentile showed a prescribing rate that was 2.6 times higher than the 10th percentile. In Online Appendix A the geographic variability in the prescribing rate across districts is depicted in Fig. A1 and an overview of all variables can be found in Table A1.

Our treatment indicator was a binary variable taking on the value of zero if the GP had the right to dispense in the year in question and a value of one otherwise. This enabled us to use “not-currently operating an OSP” as the treatment in our main model, where GPs who had a right to dispense over the entire observed period served as a control group. In our full sample, the share of GPs operating an OSP varied between 19.6% in 2019 and 20.6% in 2020. Out of the 4044 individual GPs in the full sample, 799 (19.8%) ever had the right to dispense during the observed period, thus forming the pharmacy sample. Within the pharmacy sample, 26 (3.3%) GPs had a change in dispensing status between 2016 and 2019 (11 gained and 15 lost the right to dispense). Details on the prescribing rate, OSP, as well as physician personal, patient population, and district characteristics are presented in Table 1. Comparing treatment and control group in the on-site pharmacy sample, GP gender and age groups as well as patient population characteristics were rather

similar, pointing towards always dispensing GPs as being an adequate control group.

At the physician level we also had information on GPs’ personal characteristics, practice characteristics, and patient population characteristics. We included GP gender and age, for which we defined four age groups (<45, 45–54, 55–64, 65+) to control for cohort effects reflecting, for example, changes in medical education. As the intention was to capture cohort effects, we fixed the age groups at the year 2016, making the cohort a time-unvarying variable. Next to the dispensing status we observed the number of yearly consultations as an indicator for the size of the practice.

To control for the composition and health of a GP’s general patient population, we included patient demographics and a health proxy as time-varying variables. We included the share of consultations with patients under 15, as children often catch infections for which antibiotics are prescribed (Di Martino et al., 2017). Further, the share of consultations with patients aged 65+ and with female patients were included to reflect differential needs. Lastly, the share of consultations with patients who used diabetic medication in the respective year served as a health proxy and controlled for the higher need for antibiotics, as diabetes increases the risk of contracting an infection (Casqueiro et al., 2012; Mikkelsen et al., 2015).

Additionally, we controlled for regional effects of the GP’s district, namely for the GP and specialist density, and for the population density by means of an urbanization indicator. For ease of interpretation, we

**Table 1**  
Descriptive statistics of the GP sample (2016–2019)<sup>a</sup>

	Full sample			On-site pharmacy sample		
	Never dispensing	Dispensing	Total	Control group	Treatment group	Total
Total [observations (individual GPs)]	10,948 (3245)	2793 (799)	13,741 (4044)	2691 (773)	102 (26)	2793 (799)
2016	2805	704	3509	680	24	704
2017	2764	713	3477	687	26	713
2018	2703	707	3410	681	26	707
2019	2676	669	3345	643	26	669
<i>Outcome</i>						
Prescribing rate <sup>b</sup> [Mean (SD)]	38.85 (16.16)	43.08 (16.50)	39.71 (16.32)	42.91 (16.30)	47.63 (20.64)	43.08 (16.50)
<i>GP characteristics</i>						
<i>Gender [individual GPs]<sup>c</sup></i>						
Total	3245 (100%)	799 (100%)	4044 (100%)	773 (100%)	26 (100%)	799 (100%)
Male	1991 (61%)	587 (73%)	2578 (64%)	568 (73%)	19 (73%)	587 (73%)
Female	1254 (39%)	212 (27%)	1466 (36%)	205 (27%)	7 (27%)	212 (27%)
<i>Age group in 2016 [individual GPs]<sup>c</sup></i>						
Total	3245 (100%)	799 (100%)	4044 (100%)	773 (100%)	26 (100%)	799 (100%)
<45	701 (22%)	167 (21%)	868 (21%)	162 (21%)	5 (19%)	167 (21%)
45–54	858 (26%)	227 (28%)	1085 (27%)	217 (28%)	10 (38%)	227 (28%)
55–64	1449 (45%)	373 (47%)	1822 (45%)	363 (47%)	10 (38%)	373 (47%)
65+	237 (7%)	32 (4%)	269 (7%)	31 (4%)	1 (4%)	32 (4%)
<i>Patient population characteristics</i>						
# Consultations carried out <sup>b</sup>	17,896.35 (7356.81)	18,383.85 (6833.87)	17,995.44 (7255.99)	18,305.81 (6811.99)	20,442.80 (7118.50)	18,383.85 (6833.87)
% Consultations diabetic patients <sup>b</sup>	12.07 (3.23)	12.07 (3.14)	12.07 (3.21)	12.08 (3.15)	11.68 (2.83)	12.07 (3.14)
% Consultations patients <15 <sup>b</sup>	4.13 (2.82)	5.68 (2.39)	4.45 (2.81)	5.68 (2.41)	5.58 (1.72)	5.68 (2.39)
% Consultations patients 65+ <sup>b</sup>	41.02 (10.95)	44.66 (7.28)	41.76 (10.41)	44.77 (7.28)	41.85 (6.94)	44.66 (7.28)
% Consultations female patients <sup>b</sup>	56.83 (4.50)	54.73 (3.22)	56.40 (4.35)	54.72 (3.24)	54.80 (2.87)	54.73 (3.22)
<i>District characteristics</i>						
<i>Urbanization [individual GPs]<sup>c</sup></i>						
Total	3245 (100%)	799 (100%)	4044 (100%)	773 (100%)	26 (100%)	799 (100%)
Rural	1186 (37%)	655 (82%)	1841 (46%)	634 (82%)	21 (81%)	655 (82%)
Intermediate	558 (17%)	132 (17%)	690 (17%)	129 (17%)	3 (12%)	132 (17%)
Urban	1501 (46%)	12 (2%)	1513 (37%)	10 (1%)	2 (8%)	12 (2%)
GP density <sup>b</sup>	46.60 (7.36)	51.12 (7.13)	47.52 (7.54)	51.20 (7.10)	48.87 (7.49)	51.12 (7.13)
Specialist density <sup>b</sup>	42.38 (26.23)	26.34 (10.43)	39.12 (24.74)	26.38 (10.40)	25.38 (11.35)	26.34 (10.43)

Note: Variables are measured annually on the physician level. Detailed variable description is given in Table A1 in the online appendix. Abbreviations: GP, general practitioner; SD, standard deviation.

<sup>a</sup> The GP sample consists for each year of all contracted GPs who issued at least one antibiotic prescription that was then dispensed in a public or on-site pharmacy in that year. For the year 2019, our GP sample thus corresponded to 88.5% of the total contracted GP population in Austria.

<sup>b</sup> Displayed is the mean, with standard deviation in brackets. Values are averaged across the 2016–2019 observation period.

<sup>c</sup> Displayed is the number of individual GPs, with the share of corresponding group in brackets.

Source: Own calculations based on data from Austrian Federation of Social Insurances.

used mean-centering for all non-categorical variables.

### 3. Results

Using a physician-level difference-in-differences approach, we found that having no OSP in a given year was related to significantly lower antibiotic-dispensing rates, controlling for GP personal, patient population, and regional characteristics. The estimation results from the log-linear mixed models are shown in Table 2. The *main model* accounted for a potential selection bias and was estimated using the OSP sample; hence, it included only GPs who had operated an OSP for at least one observed year. The *main model* made use of a difference-in-differences approach with dispensing GPs as control group, and GPs with a change in dispensing status as the treatment group. The *base models* did not use a difference-in-differences approach, with one using the full sample and one using the OSP sample. Logarithmic link functions were applied to the dependent variable (prescribing rate), such that coefficients can be interpreted (approximately) as semi-elasticities.

Our main variable of interest was “DID” in the *main model* and “On-site pharmacy: no” in the *base models*, both identifying non-dispensing. Results of the *base model 1* show a significant negative coefficient which might reflect self-selection into OSPs, patient sorting into dispensing practices, or unobserved differences in patient health status in more remote areas (where dispensing GPs primarily practice). To account for these potential biases, we first estimated *base model 2*

**Table 2**  
Results from a log-linear mixed model investigating the GP prescribing rate.

	Base model 1 <sup>a</sup> (full sample)	Base model 2 <sup>b</sup> (OSP sample)	Main model <sup>c</sup> (OSP sample)
Constant	3.746*** (0.021)	3.740*** (0.039)	3.737*** (0.039)
DID – On-site pharmacy (vs. yes): no			–0.097*** (0.024)
Treatment (vs. always OSP): changed status			0.073 (0.068)
On-site pharmacy (vs. yes): no	–0.078*** (0.014)	–0.093*** (0.024)	
GP characteristics	Yes	Yes	Yes
Patient population characteristics	Yes	Yes	Yes
District characteristics	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Random effects			
Physician-level	0.127	0.102	0.102
District-level	0.008	0.017	0.016
σ <sup>2</sup>	0.011	0.010	0.010
Observations	13,741	2793	2793
Marginal R <sup>2</sup> / Conditional R <sup>2</sup>	0.119/0.931	0.154/0.934	0.154/0.934

*Note:* Dependent variable is the (logarithmized) number of antibiotic (ATC code J01) prescriptions per 1000 consultations per GP (=GP prescribing rate). All numeric variables were standardized around the mean. \*, \*\*, and \*\*\* indicate significance at the 5%, 1%, and 0.1% level, respectively. Full model results including all control variables are available in Online Appendix Table B2. Abbreviations: DID, difference-in-differences; GP, general practitioner; OSP, on-site pharmacy.

<sup>a</sup> Base model 1 is a log-linear mixed model using the full sample. Full sample contains all GPs.

<sup>b</sup> Base model 2 is a log-linear mixed model using the pharmacy sample to account for potential selection bias. On-site pharmacy sample is restricted to GPs who ever had an OSP.

<sup>c</sup> Main model is a difference-in-differences log-linear mixed model using the on-site pharmacy sample to account for potential selection bias and potential group heterogeneity. On-site pharmacy sample is restricted to GPs who ever had an OSP. GPs who had an OSP in 2016–2019 are the control group, and GPs who changed OSP status during 2016–2019 are the treatment group.

*Source:* Own calculations based on data from Austrian Federation of Social Insurances.

restricting observations to the OSP sample. GPs not currently operating an OSP exhibited an 8.9% lower prescribing rate than dispensing GPs. To exploit variation in GPs switching from dispensing to non-dispensing, we estimated a difference-in-differences model (*main model*) with the OSP sample. We still observed a significant negative effect of not operating an OSP in a given year (represented by the DID variable). That is, the prescribing rate was 9.2% lower in years when GPs were non-dispensing, even when controlling for possible unobserved differences between treatment and control group. The control variable for the treatment group (GPs changing dispensing status over time) was not significant at the 5% level, revealing no marked differences between GPs who dispensed throughout the entire period 2016–2019 and those whose dispensing status changed.

The GP-specific variance component accounted for 79.7% of the total error variance in the *main model*, indicating that yearly prescription rates were more similar within, than across, GPs. So even when controlling for a number of GP and patient population characteristics, there was substantial variation across GPs. This was lower than the corresponding 87.0% in *base model 1*, suggesting that the group of dispensing GPs was less heterogeneous than the full sample. The second random effect, namely that of districts, accounted for 12.5% of total variance in the *main model*.

Robustness results are presented in Online Appendix B. The sensitivity analyses support our findings, and our *main model* is robust to different specifications.

To distinguish between a prescribing and a dispensing effect, we simulated patient behavior by explicitly modeling varying shares of unfilled prescriptions. The simulation results show the share of models that yielded a significant negative effect when estimating the main model 100 times each for ten scenarios of hypothetical unfilled prescriptions (see Table 3). All model estimates were significant for scenarios in which up to 4% of a GP’s patients are assumed to not redeem their prescriptions if they have to go to a pharmacy instead of receiving their medication at the physician’s office. Randomly dropping an average share of 1–4% of dispensing GPs’ prescriptions gave a significant negative effect of non-dispensing in 100 out of 100 models. This effect became smaller and insignificant when assuming higher rates of non-redemption behavior. Assuming an average share of 5% of unfilled prescriptions resulted in a significant negative coefficient in 31 out of 100 models, while dropping 6–10% of prescriptions yielded a significant

**Table 3**  
Results sensitivity unfilled prescriptions—summaries for 100 models per scenario.

Share randomly dropped prescriptions <sup>a</sup>	Share of models with DID-coefficient significant at 5%	Median DID-coefficient	Minimum DID-coefficient	Maximum DID-coefficient
1%	100%	–0.084	–0.082	–0.087
2%	100%	–0.076	–0.073	–0.079
3%	100%	–0.066	–0.063	–0.070
4%	100%	–0.056	–0.053	–0.059
5%	31%	–0.046	–0.042	–0.050
6%	0%	–0.035	–0.031	–0.039
7%	0%	–0.024	–0.020	–0.027
8%	0%	–0.014	–0.010	–0.017
9%	0%	–0.003	0.000	0.001
10%	0%	0.008	0.003	0.013

*Note:* For each scenario, 100 models (with shares of prescriptions dropped randomly for each model) were estimated. Table reports summary measures across the 100 models for each scenario. Abbreviations: DID, difference-in-differences; GP, general practitioner; OSP, on-site pharmacy.

<sup>a</sup> Represents the assumed mean share of unfilled prescriptions. A random share of prescriptions was dropped for each GP with an OSP; mean of the random shares reported.

*Source:* Own calculations based on data from Austrian Federation of Social Insurances.

treatment effect in 0 out of 100 models. Hence, if actual patient behavior corresponded to not filling 4% or less of antibiotic prescriptions, we would conclude that the observed effect is indeed a prescribing effect; on the other hand, we would conclude that only a dispensing effect is seen if actual patient behavior corresponded to 6% or more of unfilled prescriptions. As we cannot observe actual patient behavior, however, we cannot determine the degree to which the observed negative effect of non-dispensing captures GP prescribing behavior and the degree to which it captures dispensing differences due to patient behavior.

We can, however, investigate the potential reduction in antibiotics dispensing (either due to GP prescribing or patient redeeming behavior) that would be expected based on our main model results if all GPs operating an OSP stopped doing so. On average, a yearly reduction of 52,080 antibiotic dispensations priced above the prescription fee threshold would be expected if dispensing GPs prescribed similar to switching GPs in their non-dispensing periods. This corresponds to an average yearly reduction of 2% of all reimbursed antibiotics.

#### 4. Discussion

The findings of this empirical study support the notion that physicians with the potential to profit from dispensing medication through an on-site pharmacy exhibit higher dispensing rates. We used a sample of GPs who had had an on-site pharmacy for at least one year between 2016 and 2019, exploiting the fact that some GPs changed their dispensing status over time. Our difference-in-differences analysis revealed that the “treatment” of not operating an on-site pharmacy in a given year significantly reduced the observed dispensing rate per GP, compared to the control group of GPs who operated an OSP throughout the entire study period. GPs’ prescribing rate was 9.2% lower in years when they did not operate an OSP. The reported results held true when accounting for GP characteristics, patient population characteristics, regional heterogeneity, and time trends. Based on the model results, an average yearly 2% reduction in the overall antibiotics dispensing would be expected if all GPs operating an OSP stopped doing so. Our findings are in line with previous literature on physician dispensing such as [Kaiser and Schmid \(2016\)](#) who found an association between dispensing physicians and higher drug prices per patient in Switzerland, and [Burkhard et al. \(2019\)](#) who observed higher drug expenditures via an increased volume of drugs sold for counties which allowed physician dispensing. To investigate the causes of the observed higher antibiotic dispensing rates for GPs with an OSP, we differentiated between a prescribing effect (difference by OSP status in the number of antibiotics prescribed due to physicians’ prescribing behavior) and a dispensing effect (difference by OSP status in number of antibiotics dispensed due to patients’ prescription filling behavior). Results from a simulation showed that a pure prescribing effect would be expected if the real average share of unfilled prescriptions corresponded to 4% or less, while a pure dispensing effect would be expected if the real average share of unfilled prescriptions corresponded to 6% or more. To the best of our knowledge, we are the first to address the distinction between a prescribing effect and a dispensing effect, which is applicable to all studies that rely on reimbursement (i.e., dispensing) rather than prescription data.

There are some limitations to our analysis. Firstly, we did not observe the actual point in time of the change in OSP status for the treatment group. The change in OSP status could take place any time throughout the year, however, the reported OSP status relates to the reference date 31 December of each year. For GPs changing from non-dispensing to having an OSP, this would imply that we coded them as having an OSP for the entire year when the change occurred, whereas they may have practiced without an OSP for a part of the year. For GPs switching from having an OSP to non-dispensing, we coded them as non-dispensing for the entire year when the GP changed status, when in fact they might still have had an OSP for some time. This points to a downward bias where we underestimate the treatment effect of not operating an OSP.

Secondly, medical diagnoses are not documented in Austrian insurance claims and were thus also lacking in our data. Hence, we are not able to assess the medical appropriateness of antibiotic prescribing, unlike other studies (e.g., [Pouwels et al., 2018](#); [Zweigner et al., 2018](#)). We thus show differences in prescribing tendencies without being able to investigate over- or under-prescribing in a clinical sense.

From the analyses presented here, we cannot infer whether we observe a prescribing effect (non-dispensing GPs prescribe fewer antibiotics) or a dispensing effect (patients of non-dispensing GPs have a positive share of unfilled prescriptions while drugs are issued upon prescription for patients of dispensing GPs), as this depends on the actual (unobserved) share of unfilled prescriptions. If a prescribing effect prevails, one explanation could be demand inducement. Austrian GPs without an OSP had a median yearly income of 129,253€ in 2015 while the median income of GPs with an OSP amounted to 195,533€ ([Czypionka et al., 2018](#), p. 109). While simply operating an OSP offers opportunity for additional income — dispensing GPs earn a revenue on each medication dispensed — an OSP poses a financial incentive to prescribe generously, as further income can be generated in such a way. It should be noted here that as we used a restricted sample for potential self-selection reasons, our results (and thus potential demand inducement) apply only to the group of GPs who would choose to operate an on-site pharmacy given the chance and not necessarily to the entire GP population. A dispensing effect, however, would suggest that physicians do not engage in increased (potentially inappropriate) prescribing behavior due to financial incentives; rather, it is patients’ medication-redeeming behavior that results in different shares of filled prescriptions. This would imply that a better primary adherence could be achieved through direct dispensation on site upon prescription. In either case, higher antibiotic-dispensing patterns associated with OSPs raise concerns not only about resource efficiency, but also about patient health. The latter is especially relevant, as there are public health concerns over excessive antibiotic utilization leading to antimicrobial resistance; however, access to medication for rural populations and primary adherence to prescriptions also represent patient health concerns. Achieving a balance between access to medication for all and avoidance of inefficient and potentially harmful over-prescribing remains a challenge in healthcare systems that rely on self-dispensing providers.

#### 5. Conclusion

This study investigated the effect of on-site pharmacies on GP antibiotic dispensing exploiting changes in individual physician dispensing status within a difference-in-differences framework. Non-dispensing was significantly negatively related with antibiotic prescribing (i.e., GPs’ prescribing rate was lower in years when they did not operate an OSP). This result points toward an unintentional side-effect of facilitating access to medication in rural areas, namely that of higher antibiotic dispensing volumes.

#### Funding

Daniela Weber is a recipient of an APART-GSK Fellowship of the Austrian Academy of Sciences at the Health Economics and Policy Division of the Vienna University of Economics and Business.

#### CRedit

Barbara Stacherl: Conceptualization, Data curation, Formal analysis, Investigation, Writing – original draft Anna-Theresa Renner: Conceptualization, Methodology, Supervision, Writing – review & editing Daniela Weber: Conceptualization, Methodology, Supervision, Writing – review & editing.

## Declaration of competing interest

None.

## Data availability

The authors do not have permission to share data.

## Acknowledgments

The authors thank the Austrian Federation of Social Insurances for providing access to the data. The analyses, findings, and conclusions are solely those of the authors and do not represent the views of the Austrian Federation of Social Insurances. For data acquisition and guidance, we thank Thomas Czypionka, principal investigator of the research project that sparked the idea for this work. We also thank conference participants at the 6th ATHEA (Austrian Health Economics Association) conference for fruitful discussions and gratefully acknowledge the constructive comments of Odile Sauzet.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.socscimed.2023.115791>.

## References

- Ahammer, A., Zilic, I., 2017. Do Financial Incentives Alter Physician Prescription Behavior? *Evidence from Random Patient-GP Allocations* (Economics Working Papers No. 17–02). Department of Economics, Johannes Kepler University, Linz, Austria.
- Austria, Statistik, 2020. Bevölkerung. Retrieved May 21, 2020, from Statistik Austria. Die Informationsmanager website: [https://www.statistik.at/web\\_de/statistiken/mensch\\_und\\_gesellschaft/bevoelkerung/index.html](https://www.statistik.at/web_de/statistiken/mensch_und_gesellschaft/bevoelkerung/index.html).
- Bachner, F., Bobek, J., Habimana, K., Ladurner, J., Lepuschütz, L., Ostermann, H., et al., 2018. Austria: health system review. *Eur. Observ. Health Syst. Pol.* 20 (3).
- Baines, D.L., Tolley, K.H., Whyne, D.K., 1996. The costs of prescribing in dispensing practices. *J. Clin. Pharm. Therapeut.* 21 (5), 343–348. <https://doi.org/10.1111/j.1365-2710.1996.tb00029.x>.
- Bates, D., Mächler, M., Bolker, B., Walker, S., 2015. Fitting linear mixed-effects models using lme4. *J. Stat. Software* 67 (1). <https://doi.org/10.18637/jss.v067.i01>.
- Björkman, I., Berg, J., Viberg, N., Stålsby Lundborg, C., 2013. Awareness of antibiotic resistance and antibiotic prescribing in UTI treatment: a qualitative study among primary care physicians in Sweden. *Scand. J. Prim. Health Care* 31 (1), 50–55. <https://doi.org/10.3109/02813432.2012.751695>.
- Bodnar, O., Gravelle, H., Gutacker, N., Herr, A., 2021. *Financial Incentives and Prescribing Behaviour in Primary Care* [Working Paper]. Center for Health Economics, University of York, York, UK.
- Brabers, A.E., Van Esch, T.E., Groenewegen, P.P., Hek, K., Mullenders, P., Van Dijk, L., De Jong, J.D., 2018. Is there a conflict between general practitioners applying guidelines for antibiotic prescribing and including their patients' preferences? *Patient Prefer. Adherence* 12, 9–19. <https://doi.org/10.2147/PPA.S147616>.
- Burkhard, D., Schmid, C.P.R., Wüthrich, K., 2019. Financial incentives and physician prescription behavior: evidence from dispensing regulations. *Health Econ.* 28 (9), 1114–1129. <https://doi.org/10.1002/hec.3893>.
- Casqueiro, J., Casqueiro, J., Alves, C., 2012. Infections in patients with diabetes mellitus: A review of pathogenesis. *Indian J. Endocrinol. Metab.* 16 (7), 27. <https://doi.org/10.4103/2230-8210.94253>.
- Chandra, A., Cutler, D., Song, Z., 2011. Who ordered that? The economics of treatment choices in medical care. *Handb. Health Econ.* 2, 397–432. <https://doi.org/10.1016/B978-0-444-53592-4.00006-2>. Elsevier.
- Chou, Y., 2003. Impact of separating drug prescribing and dispensing on provider behaviour: Taiwan's experience. *Health Pol. Plann.* 18 (3), 316–329. <https://doi.org/10.1093/heapol/czg038>.
- Czypionka, T., Pock, M., Reiss, M., 2018. *ÄrztInneneinkünfte Österreich. Eine Analyse anhand von Lohn- und Einkommensdaten*. Institute for Advanced Studies, Vienna, pp. 1–207 [Project Report].
- Dekker, A.R.J., Verheij, T.J.M., van der Velden, A.W., 2015. Inappropriate antibiotic prescription for respiratory tract indications: most prominent in adult patients. *Fam. Pract. cmv019*. <https://doi.org/10.1093/fampra/cmv019>.
- Di Martino, M., Lallo, A., Kirchmayer, U., Davoli, M., Fusco, D., 2017. Prevalence of antibiotic prescription in pediatric outpatients in Italy: The role of local health districts and primary care physicians in determining variation. A multilevel design for healthcare decision support. *BMC Public Health* 17, 886. <https://doi.org/10.1186/s12889-017-4905-4>.
- Ekedahl, A., Månsson, N., 2004. Unclaimed prescriptions after automated prescription transmittals to pharmacies. *Pharm. World Sci.* 26 (1), 26–31. <https://doi.org/10.1023/B:PHAR.0000013464.09197.41>.
- Elbasha, E.H., 2003. Deadweight loss of bacterial resistance due to overtreatment. *Health Econ.* 12 (2), 125–138. <https://doi.org/10.1002/hec.702>.
- Ellegård, L.M., Dietrichson, J., Anell, A., 2018. Can pay-for-performance to primary care providers stimulate appropriate use of antibiotics?: can P4P stimulate appropriate use of antibiotics? *Health Econ.* 27 (1), e39–e54. <https://doi.org/10.1002/hec.3535>.
- Filippini, M., Heimsch, F., Masiero, G., 2014. Antibiotic consumption and the role of dispensing physicians. *Reg. Sci. Urban Econ.* 49, 242–251. <https://doi.org/10.1016/j.regsciurbeco.2014.07.005>.
- Hillman, A.L., 1990. Health maintenance organizations, financial incentives, and physicians' judgments. *Ann. Intern. Med.* 112 (12), 891. <https://doi.org/10.7326/0003-4819-112-12-891>.
- Iizuka, T., 2007. Experts' agency problems: evidence from the prescription drug market in Japan. *Rand J. Econ.* 38 (3), 844–862 (JSTOR). Retrieved from JSTOR.
- Iizuka, T., 2012. Physician agency and adoption of generic pharmaceuticals. *Am. Econ. Rev.* 102 (6), 2826–2858. <https://doi.org/10.1257/aer.102.6.2826>.
- Kaiser, B., Schmid, C., 2016. Does physician dispensing increase drug expenditures? Empirical evidence from Switzerland. *Health Econ.* 25 (1), 71–90. <https://doi.org/10.1002/hec.3124>.
- Kardas, P., Cieszyński, J., Czech, M., Banaś, I., Lewek, P., 2019. Primary non-adherence to medication and its drivers of in Poland: findings of the analysis of the e-prescription pilot. *Pol. Arch. Intern. Med.* <https://doi.org/10.20452/pamw.14994>.
- Kennedy, J., Tuleu, I., Mackay, K., 2020. Unfilled prescriptions of medicare beneficiaries: prevalence, reasons, and types of medicines prescribed. *J. Manag. Care Spec. Pharm.* 26 (8), 935–942. <https://doi.org/10.18553/jmcp.2020.26.8.935>.
- Liu, Y.-M., Yang, Y.-H.K., Hsieh, C.-R., 2009. Financial incentives and physicians' prescription decisions on the choice between brand-name and generic drugs: evidence from Taiwan. *J. Health Econ.* 28 (2), 341–349. <https://doi.org/10.1016/j.jhealeco.2008.10.009>.
- Llor, C., Bjerrum, L., 2014. Antimicrobial resistance: risk associated with antibiotic overuse and initiatives to reduce the problem. *Therapeut. Adv. Drug Saf.* 5 (6), 229–241. <https://doi.org/10.1177/2042098614554919>.
- Martens, J.D., Werkhoven, M.J., Severens, J.L., Winkens, R.A.G., 2007. Effects of a behaviour independent financial incentive on prescribing behaviour of general practitioners. *J. Eval. Clin. Pract.* 13 (3), 369–373. <https://doi.org/10.1111/j.1365-2753.2006.00707.x>.
- McGuire, T.G., 2000. Physician agency. In: Culyer, A.J., Newhouse, J.P. (Eds.), *Handbook of Health Economics, first ed., Vol. 1*. Elsevier, pp. 461–536.
- Mikkelsen, K.H., Knop, F.K., Frost, M., Hallas, J., Pottegård, A., 2015. Use of Antibiotics and Risk of Type 2 Diabetes: A Population-Based Case-Control Study. *J. Clin. Endocrinol. Metab.* 100 (10), 3633–3640. <https://doi.org/10.1210/jc.2015-2696>.
- Müller, T., Schmid, C., Gerfin, M., 2022. Rents for pills: financial incentives and physician behavior. *SSRN Electron. J.* <https://doi.org/10.2139/ssrn.4066408>.
- Nowakowska, M., van Staa, T., Mølter, A., Ashcroft, D.M., Tsang, J.Y., White, A., Palin, V., 2019. Antibiotic choice in UK general practice: rates and drivers of potentially inappropriate antibiotic prescribing. *J. Antimicrob. Chemother.* 74 (11), 3371–3378. <https://doi.org/10.1093/jac/dkz345>.
- Park, S., Soumerai, S.B., Adams, A.S., Finkelstein, J.A., Jang, S., Ross-Degnan, D., 2005. Antibiotic use following a Korean national policy to prohibit medication dispensing by physicians. *Health Pol. Plann.* 20 (5), 302–309. <https://doi.org/10.1093/heapol/czi033>.
- Pouwels, K.B., Dolk, F.C.K., Smith, D.R.M., Robotham, J.V., Smieszek, T., 2018. Actual versus “ideal” antibiotic prescribing for common conditions in English primary care. *J. Antimicrob. Chemother.* 73 (Suppl. 12), 19–26. <https://doi.org/10.1093/jac/dkx502>.
- R Core Team, 2020. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria. Retrieved from. <https://www.R-project.org/>.
- Rischatsch, M., Trottmann, M., Zweifel, P., 2013. Generic substitution, financial interests, and imperfect agency. *Int. J. Health Care Finance Econ.* 13 (2), 115–138. <https://doi.org/10.1007/s10754-013-9126-5>.
- Sydenham, R.V., Jarbøl, D.E., Hansen, M.P., Justesen, U.S., Watson, V., Pedersen, L.B., 2022. Prescribing antibiotics: factors driving decision-making in general practice. A discrete choice experiment. *Soc. Sci. Med.* 305, 115033 <https://doi.org/10.1016/j.socscimed.2022.115033>.
- WHO, 2000. In: *The World Health Report 2000. Health Systems: Improving Performance*. World Health Organization, Geneva.
- Wickham, H., 2016. *ggplot2: Elegant Graphics for Data Analysis*. Springer-Verlag, New York. <https://doi.org/10.1007/978-3-319-24277-4>.
- Wickham, H., Francois, R., Henry, L., Müller, K., 2020. *Dplyr: a grammar of data manipulation*. R package version 1.0.1. Retrieved from. <https://CRAN.R-project.org/package=dplyr>.
- Zweigner, J., Meyer, E., Gastmeier, P., Schwab, F., 2018. Rate of antibiotic prescriptions in German outpatient care – are the guidelines followed or are they still exceeded? *GMS Hyg. Infect. Control* 13, Doc04. <https://doi.org/10.3205/DGKH000310>.