Patient-driven Information Flow and Practice Style Spillover

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Abstract

This paper studies how physicians form and update prescribing behavior under uncertainty. Using quasi-random patient reallocation following primary care clinic closures in Denmark, I examine whether antibiotic prescribing practice styles are transmitted across clinics through patient mobility. I find that clinics receiving more new patients with prior antibiotic use increase their own prescribing intensity to existing patients, with a twofold increase in such patients raising prescribing by 2.3 percent. The response is stronger among newer clinics and is accompanied by increased use of diagnostic tests. The results are consistent with physicians learning from the prescribing histories of incoming patients rather than responding solely to changes in patient volume. Overall, the findings highlight patient mobility as an important, informal channel of information transmission in healthcare markets and suggest that prescribing practices may diffuse across clinics through patient reallocation. These spillovers have implications for the persistence of practice variation and for the design and evaluation of policies aimed at improving antibiotic stewardship.

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1 Introduction

Healthcare providers exhibit substantial and persistent variation in the quality and intensity of care they deliver. A large body of research documents wide differences in treatment choices, spending, and outcomes across physicians and healthcare markets, even for clinically similar patients (e.g., Chandra et al. 2011; Finkelstein et al. 2016; Fadlon and Van Parys 2020; Huang and Ullrich 2023). Such variation is difficult to reconcile with demand-side differences in patient preferences or medical need alone and raises concerns about inefficiencies and unequal access to better care.

A key supply-side driver for this variation is heterogeneity in physician beliefs (Cutler et al. 2019) and information. Gaps in knowledge, uncertainty about appropriate treatment, and limited diffusion of best practices play a central role in shaping provider behavior through updating beliefs (Phelps 1992; Arrow et al. 2020). When physicians face different levels of information about diagnosis, treatment effectiveness, or peer practices, patient care can vary across providers even for similar underlying conditions. Understanding how physicians acquire and update information is therefore critical for evaluating policies aimed at reducing unwarranted variation and improving healthcare quality.

Physicians can acquire information through multiple channels. Formal medical training and continuing education shape baseline knowledge, while clinical guidelines and decision-support tools provide standardized recommendations. Information may also diffuse informally through interaction with peers in team practices, professional networks, or referral relationships (Coleman et al. 1957; Chen 2021; Agha et al. 2022). Clinical databases and scientific publications also provide information generated by peer physicians, facilitating adoption of new technologies and treatments (Epstein and Ketcham 2014; Agha and Molitor 2018; Arrow et al. 2020).

In this paper, I focus on a distinct channel of information transmission: patient mobility across primary care clinics. When patients move between providers, they bring with them realized treatment histories, including prior diagnoses and prescriptions. These histories can serve two informational roles for receiving physicians. First, they provide realized outcomes that may reduce diagnostic or treatment uncertainty, particularly in cases where symptoms persist or treatments fail. Second, they act as credible signals of how peer physicians have treated similar cases, revealing prevailing practice styles in the local medical market. Unlike guidelines or formal communication, this information is sourced from routine clinical encounters and may influence decision-making even in the absence of explicit discussion between physician peers.

I investigate whether this information channel affects physicians' decisions in the context of antibiotic prescribing in primary care, using administrative data covering the universe of patients and primary care clinics from 2014 to 2019 in Denmark. Antibiotic prescribing is a particularly relevant and informative outcome, primarily because it has clear quality dimensions. Inappropriate prescribing, whether due to patient pressure, diagnostic uncertainty, or practice style, has been identified as a key driver of antimicrobial resistance, a mounting global health crisis (Laxminarayan et al. 2013). Broad-spectrum antibiotics, in particular, are often prescribed in cases where narrower alternatives would be clinically sufficient. As a result, changes in antibiotic prescribing behavior have direct welfare implications, making this outcome especially relevant from a policy perspective.

Furthermore, prescribing decisions are often made with limited diagnostic information, requiring physicians to rely on experience and informal signals. In Denmark, primary care physicians act as gatekeepers of antibiotics, and account for 88% of the total antibiotics prescribed in 2024.[1] However, antibiotic prescribing exhibits large and persistent variation across physicians and clinics that is difficult to reconcile with differences in patients' medical need (Huang and Ullrich 2024). To promote rational and efficient use of antibiotics, the Danish Health and Medicines Authority issued a guideline[2] for physicians in 2013. Nevertheless, physicians often need to rely on their own skills and experience to determine the treatment, especially when diagnostic tests for bacterial infection are delayed or unavailable (Ribers and Ullrich 2023), which may result in unwarranted variation in antibiotic use. Hence, understanding how prescribing behaviors form and change is essential for designing effective interventions.

Empirically isolating the effect of information transmitted through patient flows is challenging because patient movements are typically endogenous to physician behavior and clinic characteristics. To address this endogenous selection, I exploit quasi-random patient reallocation following primary care clinic closures in Denmark. Clinic closures force patients to seek care elsewhere, generating plausibly exogenous variation in both the number and composition of incoming patients across clinics. I identify clinic closures and patient switches using Danish administrative data on the universe of patients and primary care clinics from 2014 to 2019, and then construct a shift-share style instrument to measure exposure to the closed clinics' antibiotic prescribing styles through patient arrivals. Instrumenting for the prescribing history of newly arrived patients, I find that receiving double the number of patients with an antibiotic prescribing history increases the overall antibiotic prescribing intensity for existing patients at the receiving clinic by 2.3 percent, and has a larger effect among newer clinics. The heterogeneous effect of information on clinics with different levels of experience aligns with Bayesian learning models that predict a stronger response to new signals in agents with less prior information.[3] This increase does not come at the cost of care quality and access, as I find positive effects on both testing and pre-testing prescribing intensities for existing patients as well, but no evidence on prescriptions that require subsequent corrections.

[1] Summary Report 2024, The Danish Integrated Antimicrobial Resistance Monitoring and Research Programme (DANMAP), https://www.danmap.org/-/media/institutter/foedevareinstituttet/danmap-site/report-2024/summary_danmap_2024_full-report_low-vesion-2.pdf

[2] Guidelines on prescribing antibiotics for physicians and others in Denmark, the Danish Health and Medicines Authority, https://www.sst.dk/media/4b5het54/guideline-on-prescribing-antibiotics.pdf. Last accessed 13/01/2026.

[3] For example, Rockoff et al. (2012) finds that school principals with less precise prior beliefs change their evaluation of teacher productivity more after receiving an external performance measure of the teachers. Bhuller and Sigstad (2025) shows that after learning reversals in appeal decisions, less experienced judges and judges who have not processed a similar case before react more by adjusting their sentencing for future cases. In the healthcare context, Coscelli and Shum (2004) and Crawford and Shum (2005) show that prior beliefs about the drug effectiveness are refined over time once physicians and patients start to observe the treatment outcomes. Although they did not explicitly parameterize updating by physician experience, both models suggest that responses to new signals depend on the priors accumulated over time.

By documenting how prescribing styles respond to information from patient histories, this paper contributes to the literature on physician learning and information acquisition by highlighting patients as an additional source of signal. A growing body of work has shown that physicians update beliefs based on accumulated experience and imperfect signals, particularly in the context of new or generic drug diffusion. These signals include responses from their own patients as well as information recorded in administrative or clinical databases on treatment outcomes for other patients (Coscelli and Shum 2004; Epstein and Ketcham 2014; Arrow et al. 2020; Zhu 2023). Related learning processes also occur on the demand side, where patients update beliefs about drug effectiveness through own experience, social networks, and word-of-mouth (Crawford and Shum 2005; Ching 2010). In addition, literature has documented positive returns to experience in surgical settings, showing that physicians or hospitals performing more procedures achieve better outcomes (Gaynor et al. 2005; Avdic et al. 2019; Domenella 2025). This series of "volume-outcome" literature primarily emphasizes learning from within-physician (or clinic) signals over time that also generates a positive spillover to other patients. In contrast, this paper identifies a learning mechanism that operates through exposure to patients previously treated by other physicians.

This paper also provides empirical evidence of a mechanism that drives the documented persistent variation in healthcare provision across providers. Prior studies have shown large and systematic differences in treatment intensity and quality at the provider level across geography (Chandra and Staiger 2007; Finkelstein et al. 2016). Others have also found substantial within-region variations in care delivery, driven by provider practice styles (Fadlon and Van Parys 2020; Huang and Ullrich 2023), and in some cases considerably larger than variations across regions (Epstein and Nicholson 2009). While these studies establish a provider-specific factor that contributes to the persistence of practice variation, relatively few papers explore how these practice styles are formed. Among these papers, some have attributed the differences in treatment styles to environmental and regional factors, such as hospital capacity, productivity, and local policies (Chandra and Staiger 2007; Epstein and Nicholson 2009; Molitor 2018). Other studies have shown that financial incentives and market competition can shift treatment decisions, without explicitly translating the observed effect to practice styles (Currie et al. 2014; Bennett et al. 2015). In this paper, I show that information brought by incoming patients facilitates the transmission of clinic-specific prescribing norms and can change the receiving clinics' prescribing decisions, potentially leading to convergence of practice styles over time and geography.

Finally, this paper relates to the broader literature on peer effects and knowledge spillovers. Previous literature has documented that physician behavior responds to interactions with peers, referral networks, and local professional environments (Coleman et al. 1957; Chen 2021; Agha et al. 2022). Similarly, spillovers occur through direct interactions in other social settings. For example, Sorensen (2006) finds that coworkers learn about their healthcare plans and converge towards the same choices. Another example from Bailey et al. (2022) in the consumer market shows that people are more likely to purchase phones of the same brand following a recent purchase by their friend. This paper extends the peer effects literature by demonstrating that knowledge spillovers need not operate through direct communication or social networks. Instead, patients can transmit information across providers, allowing physicians to infer peer practices indirectly. This mechanism complements existing evidence on learning through professional interaction and suggests that informal information flows may play an important role in shaping provider behavior.

2 Institutional Background and Data

2.1 Institutional Background

Danish public health insurance has universal coverage of visits and services from primary care providers, who are usually general practitioners (or known as family doctors). General practitioners can take care of minor health issues and health maintenance. Additionally, the general practitioner also acts as a gatekeeper for other healthcare services such as prescriptions for drugs, referrals to other specialists, and hospital inpatient treatments. There are about 3,500 general practitioners in Denmark, each treating about 1,600 patients (Simonsen et al. 2021). Approximately 2,200 clinics are run by general practitioners, among which approximately 1,300 are single-physician clinics (Simonsen et al. 2021). Each primary care provider has to acquire a practice authorization number to claim reimbursement from public health insurance. The state has control over the number of practice authorizations based on factors such as the population density in a given area.

Primary care providers are self-employed and are responsible for the revenue of their clinics. A clinic's income is composed of two parts: a fixed fee per listed patient, i.e. capitation, which accounts for about one-third of their income, and fee-for-service payments that make up the rest. Physicians do not have agency over the fees they charge. Instead, the Danish Medical Association and the government negotiate the charges every third year (with biannual price adjustments). Notably, physicians do not receive additional fees directly related to prescriptions.

Every resident in Denmark is required to join the patient list of a primary care clinic, typically located within a 15 km radius of their residence[4], which will serve as their designated contact in case of medical needs. Physicians cannot selectively reject individual patients as long as they have not reached a capacity limit of 1600.[5] Physicians can stop accepting new patients when they have 1600 patients on their list. Patients can change their initially listed practice for a fee (DKK 150, about USD 20). Only the physician's name and the clinic address are publicly observed, so that selective switching between primary care clinics is difficult (Huang and Ullrich 2023).

In the case of a closure, the entire patient list, often together with the physical practice, can be sold to the newcomer physician or clinic. If no such takeover occurs, patients of the closing clinics are randomly assigned to nearby practices that are accepting new patients. Closures do not need to be communicated to the patients in advance, but patients are notified of clinics that are open for new patients within the 15 km limit, and the local government is obliged to ensure

[4] 5 km in densely populated areas such as central Copenhagen.
[5] In some cases, this capacity limit may not be binding so that some physicians have over 1600 patients on their lists.

that at least two practices are available in their choice sets. When patients switch to a new clinic, their records are transferred automatically, unless they explicitly deny the transfer within the first 14 days after the switch. This feature is crucial for the identification of the information transmission, as it guarantees that the receiving clinics have access to both documented and self-communicated treatment histories from switching patients.

2.2 Data and Sample Construction

I use authorization numbers from the Danish Clinic Registry (Yderregisteret), matched to claims data from the Danish National Outpatient Claims Registry (Sygesikringsregistret), to identify primary care clinics. The Clinic Registry reports, for each clinic, opening and closing dates, postcode, and the unique personal identification numbers (personnummer, PNR[6]) of physicians and other healthcare workers affiliated with the clinic. The Claims Registry contains clinic authorization numbers, the date a claim is filed, patient identifiers (PNR), and the types of medical services provided. Medical services are recorded using six-digit codes, which allow me to identify services that are exclusively provided by the primary care sector.

I define each patient's choice of primary care clinic and identify switching behavior following the algorithm proposed by Kjaersgaard et al. (2016). The algorithm uses general practice service records from the Claims Registry to assign patients to clinics over time based on observed patient–provider encounters. Specifically, patients are linked to the clinic providing their general practice services, and continuous patient–clinic affiliation intervals are constructed using the timing and provider identifiers of these services. Very short affiliation spells (less than 31 days) are removed to focus on sustained relationships, and the resulting intervals are aggregated to 3 calendar months to create a consistent quarterly panel, where each patient is assigned to exactly one primary care clinic.[7] A patient is defined as switching clinics when the assigned clinic changes from one quarter to the next. This procedure closely replicates the official Patient List Database and provides a reliable measure of patient choice and switching over time.

The outcome variables and prescribing histories are constructed using prescription data from the Danish National Prescription Registry (Lægemiddeldatabasen, LMDB). This registry records every prescription redeemed at Danish pharmacies, including the drug name, brand, quantity, dispensing date, clinic authorization number, and patient PNR. I then link the Clinic Registry, claims data, and prescription data using the clinic authorization numbers to construct a clinic-level panel of claims and prescribing activity. I further use this panel to infer missing information for some clinics. For example, for clinics without a recorded closing date in the Clinic Registry, I assume that they remain active until there is a sharp and sustained decline in prescription volumes, typically accompanied by a similar decline in claims. Together with the patient list built from the Claims Registry, I obtain a preliminary sample of 2207 primary care clinics with complete information on clinic activities, characteristics and patient compositions from 2014 to 2019.

[6] The PNR is the unique pseudonomized identifying number assigned to all residents of Denmark.

[7] I drop weeks with services from multiple clinics to avoid ambiguous assignments, in line with Kjaersgaard et al. (2016).

I use forced displacement of patients following clinic closures to instrument for the potentially endogenous switching decisions of the patients. To construct the instrumental variable, I first identify patients at the closing clinics who show up at different clinics within 4 quarters of the closing date of their original clinics. These patients constitute an exogenous source of information flows arriving at the receiving clinic. Then I exclude transition periods where the destination clinics potentially take over the closed clinics, as clinics that replace an existing clinic do not have an existing pool of non-switching patients to study their outcomes.[8] I assume a new clinic is a takeover when it is at the same location as a closed clinic, and its entry date is in the same or next quarter in which the closure happens. I drop the periods where they receive more patients from exiting clinics than non-switchers. Similarly for both existing and other new clinics that are not takeovers, I remove the periods where they do not have a sufficiently large number of non-switching patients to identify any changes to their prescribing patterns.[9] Finally, to reduce noise arising from sparse observations and to avoid mechanically large ratios driven by small denominators, I exclude observations with very small base values. When constructing share-based measures such as the prescribing intensity and the share of patients with prior prescriptions among newly received patients, I drop clinic-quarter period observations with a low number of consultations and new patients.[10]

2.3 Descriptive Statistics

My final sample contains 5,011,537 patients assigned to 1,838 active primary care clinics from 2014 to 2019. The majority of the clinics in the sample (87%) were established before the first quarter of 2014, the earliest sample date. Among all clinics opened before the first quarter of 2014, 1,152 remained active until the final quarter of 2019, including 581 clinics that had complete records for every quarter. During the sample period between 2014 and 2019, 248 new clinics opened, meanwhile a total of 374 clinics closed permanently, which is larger than the total number of openings. The clinics in the sample thus align with the nationwide decreasing trend in the number of primary care clinics, as shown in Figure 2.1. However, the average number of physicians in a clinic has been rising. The growing size of clinics may also facilitate internal information exchange among physicians, so that they rely less on external signals.[11]

Table 2.1 summarizes descriptive statistics of the clinic-quarter sample. A primary care clinic has on average 2.2 physicians and around 3100 listed patients. The average number of patients per physician is very close to what previous literature has documented (1600), supporting the quality of the matching algorithm. During 2014 to 2019, an average clinic filed around 8800

[8] As a robustness check, I also estimate the main regression on two subsamples. First, I exclude all observations of clinics that are takeovers and for the other I exclude all newly entered clinics between 2014 and 2019. The results are in Appendix Table D.11.

[9] Specifically, I drop clinic-quarter observations in the bottom 5% in terms of the number of non-switching patients.

[10] For the number of consultations from the non-switchers, I drop observations with less than 50 consultations per quarter (bottom 5%). I also drop quarters where the clinic receives fewer than 5 new patients to reduce noise as well as to ensure anonymity.

[11] In Appendix Table D.14 I show that single-physician clinics' prescribing intensity increases more when exposed to incoming patients with prior prescriptions, while multi-physician clinics almost do not respond.

Table 2.1: Clinic descriptive statistics

	mean	s.d.
Number of clinics	1399.87	96.23
Total number of listed patients	3078.23	1848.15
Number of visited patients	2308.67	1492.47
Number of antibiotic prescriptions	296.73	200.87
Defined daily dose (DDD)	2995.73	2026.52
Number of claims	8782.97	5758.08
Number of consultations	2919.05	1857.91
Number of prescriptions per consultation	0.10	0.04
Number of claims per physician	4152.76	1404.94
Clinic size	2.18	1.34
Share of female physicians	0.49	0.40
Physician age	53.66	7.84
Physicians with immigration background	0.08	0.24
Years since entry	21.32	14.18
Non-switching patients		
Number of non-switching patients	2118.54	1663.17
Share of non-switching patients	0.65	0.26
Number of antibiotic prescriptions	173.28	153.90
Number of consultations	1856.51	1578.89
Number of claims	5480.88	4719.56
Number of prescriptions per consultation	0.10	0.04
Other patients		
Number of new patients	52.02	66.91
Share of new patients with prescriptions	0.30	0.13
Number of prescriptions per consultation	0.12	0.05
Observations	32197	

Note: This table summarizes the mean and the standard deviation of the listed variables from an unbalanced quarterly panel consisting of 1,838 active primary care clinics from 2014 to 2019. Clinic size refers to the number of physicians in a clinic, excluding other supportive roles such as assistants, administrative staff, and interns. Physicians with immigration background include physicians who are first- or second-generation immigrants.

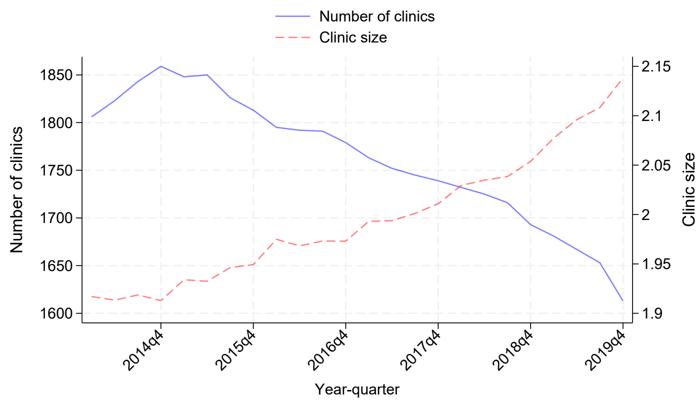


Figure 2.1: Number of primary clinics and average clinic size

Notes: This graph illustrates the development in the number of primary care clinics and clinic size in Denmark, during 2014-2019. Clinic size is defined as the number of physicians actively practicing in a given quarter, excluding other supportive roles such as assistants, administrative staff, and interns. Primary care clinics are considered active if they file claims and issue a reasonable number of prescriptions. Clinics that did not file any claims in a given quarter are considered inactive and are dropped.

claims per quarter, 28.0% of which were consultations. I distinguish consultations from other types of medical services because they serve as a proxy for the frequency of patient visits, and also because the majority of antibiotic prescriptions in primary care are given during consultations. Other types of treatments that primary care clinics carry out and file claims for include referrals to specialists and follow-ups of the previous treatment. Variation in the number of claims and consultations across clinics is mostly due to variation in clinic size as, by design, bigger clinics with more physicians have a larger capacity to admit patients. Hence, when analyzing primary care clinics' medical service provision, I net out the effect of clinic size or the number of patients by averaging the total number of prescriptions over the number of consultations at a given time and clinic.

The bottom two panels of Table 2.1 report descriptive statistics at the clinic level, distinguishing between non-switching and new patients. Clinics serve a large and stable base of non-switching patients, with an average of around 2,100 such patients per clinic and a mean share of 65% of the patient population. This stability is also reflected in high levels of patient activity, where non-switching patients account for an average of 1,856 consultations and 173 antibiotic prescriptions per clinic. Despite substantial variation across clinics, as indicated by the large standard deviations, prescribing intensity for non-switching patients is relatively stable, with an average of 0.10 prescriptions per consultation.

In contrast, clinics receive a much smaller inflow of new patients. On average, clinics see 52 new patients per quarter, who constitute a considerably smaller share of the patient population. Among these incoming patients, 30% have a prior history of antibiotic prescriptions. The substantial variation in both the number of new patients and their prior prescribing histories generates heterogeneity in the information arriving at receiving clinics. Once they are admitted, new patients are more likely to receive a prescription conditional on a consultation, with a

Table 2.2: Share of patient types

Non-switchers	2,357,826	47%
Switchers	2,653,711	53%
Switch due to clinic closure	919,424	18%
Switch due to move	732,412	15%
Switch due to other reasons	1,001,875	20%

mean of 0.12 prescriptions per consultation, compared to non-switching patients. As prescribing intensity may reflect care quality, especially in settings where antibiotic use is encouraged to be targeted and low, this higher mean may signal a less selective prescribing to newly arrived patients.

Table 2.2 summarizes the switching decisions among patients in the sample. Switchers are patients who have changed their primary clinics at least once based on the matching algorithm described in Section 2.2. Non-switchers are patients who remain with the same clinic during the sample period. More than half (53%) of the patients moved to a different clinic at least once in 6 years between 2014 and 2019, and one-third of them switched because their previous clinics had closed. Another third of the switchers changed clinics because they moved to different home addresses. Table 2.3 compares the characteristics of switching and non-switching patients. While switchers, on average, receive fewer antibiotic prescriptions and have fewer consultations per person, the two groups are otherwise broadly comparable in terms of healthcare utilization and demographic characteristics. There are higher shares of female patients and patients with immigration background among switchers, and patients who switch are also younger, with a mean age of 38 at the time of their switches.

Figure 2.2 plots the distribution of the changes in distances to the clinics after switching to a new clinic. The majority of patients move to clinics closer than their original clinics, and patients are more likely to switch within the vicinity of their home address, as shown by the concentration around a 1 km difference in distance. Furthermore, Figure 2.3 suggests that patients' choice of clinic does not appear to be dependent on prescribing patterns, and if anything, more patients switch to clinics with lower average prescribing intensities than their original clinics. These figures, together with the decomposition of reasons for switching presented in Table 2.3, lend confidence to the assumption that switching is likely triggered by factors exogenous to a clinic's performance rather than selective sorting based on prescribing behaviors.

I further present two stylized facts that characterize switching patients and their receiving clinics in Figure 2.4. First, the share of new patients with prior antibiotic prescribing is proportional to the number of new patients at the receiving clinic. As shown in Figure 2.4a, doubling the number of new patients increases the likelihood of receiving a patient who comes with a prescribing history by 2 percentage points. In other words, the more new patients that come to a

Table 2.3: Patient descriptive statistics

	mean (s.d.)	
	Non-switchers	Switchers
Number of antibiotic prescriptions	1.32	1.29
	(0.79)	(0.72)
Number of consultations	1.94	1.91
	(1.53)	(1.44)
Number of claims	4.41	4.29
	(4.37)	(4.15)
Share of female patients	0.51	0.55
	(0.50)	(0.50)
Patient age	43.29	39.53
	(24.09)	(22.72)
Share of patients with immigration background	0.10	0.13
	(0.31)	(0.33)
Number of switches		1.34
		(0.67)
Age when switching		38.22
		(22.47)
Observations	121,250,996	

Note: This table summarizes the mean and the standard deviation of the listed variables from an unbalanced quarterly panel consisting of 5,011,537 patients assigned to 1,838 active primary care clinics from 2014 to 2019. Patients with immigration background include patients who are first- or second-generation immigrants.

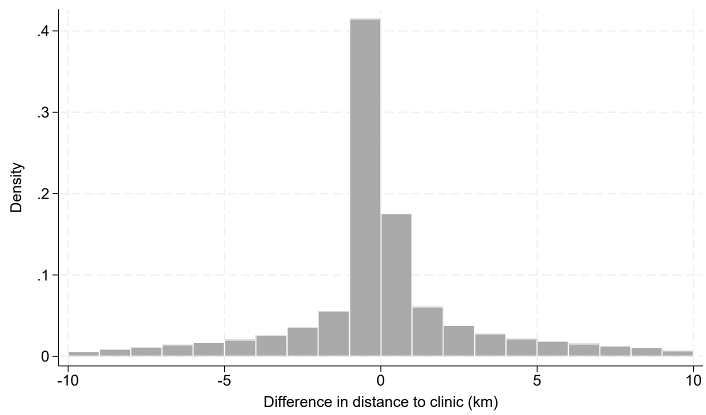


Figure 2.2: Difference in home distance to new and original clinic

Notes: Distances are calculated from the WGS84 (World Geodetic System 1984) coordinates of pseudonomized residential and clinic addresses using the Haversine formula method. Differences in distances to the chosen clinics are calculated for each switch observed during the sample period, and trimmed at +/- 10km to ensure anonymity.

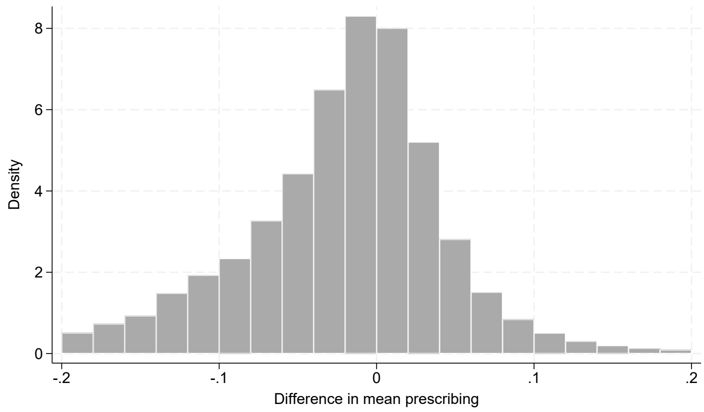


Figure 2.3: Difference in prescribing style between new and original clinic

Notes: Prescribing style of a clinic is defined as the mean antibiotic prescribing intensity among non-switching patients over all observations of a given clinic. Prescribing intensities are calculated from the number of antibiotic prescriptions over the number of consultations. Differences in prescribing styles are trimmed at +/- 0.2 to ensure anonymity.

clinic, the more likely the clinic is exposed to information specific to the prescribing practices of other clinics. Second, I show that the arrival of new patients is not correlated with the receiving clinic's past prescribing intensity in Figure 2.4b. There is a small and statistically insignificant negative correlation between prescribing intensity in the period before patient arrival and the number of new patients. Together with the overall switching pattern of patients moving to clinics with lower mean prescribing intensity depicted in Figure 2.3, this additional evidence again supports that patients do not actively sort on the prescribing behaviors of the receiving clinics.

3 Empirical strategy

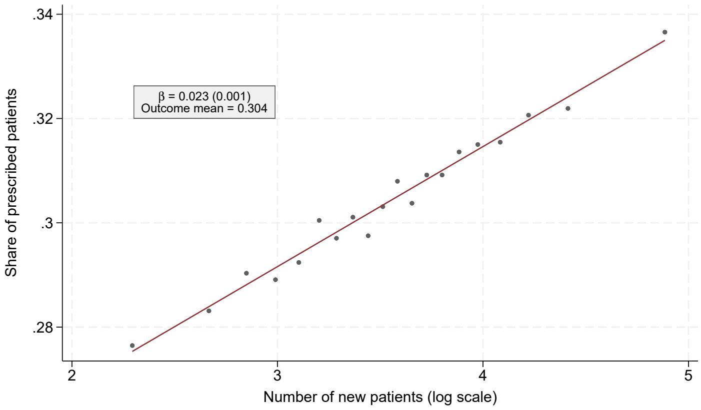
3.1 Measure for exposure to information

To measure the effect of information from new patients on antibiotic prescribing at the receiving clinic, I define two closely related information measures using the incoming patients and their prescribing histories. First, for each receiving clinic in each quarter, I measure the size of the information inflow by counting the number of new patients with any prior antibiotic prescription at their origin clinics:

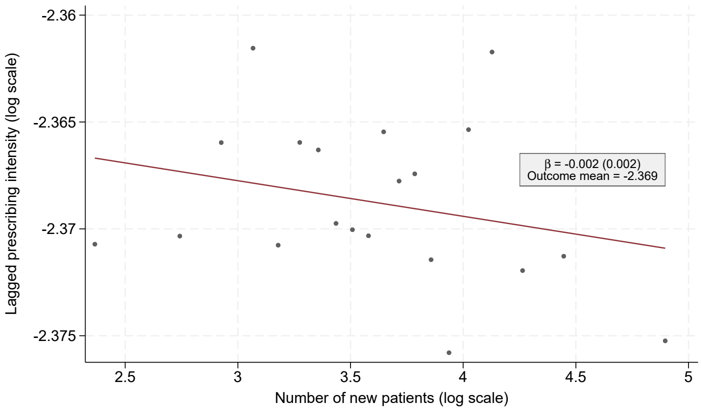
$$volume_{it} = \sum_{j=1}^{J} (prescribed_{jt} \times switch_{ijt})$$

Here, $prescribed_{jt} \in \{0, 1\}$ is an indicator for patient j receiving an antibiotic prescription from their previous clinics before switching at t.

In addition to the volume-based measure, a second information variable measures the intensity of information exposure using the share of incoming patients who were prescribed the treatment by their previous physicians, among all the new patients that the clinic received in a



(a) Relationship between number of new patients and share of prescribed new patients



(b) Relationship between lagged prescribing intensity and number of new patients

Figure 2.4: Arrival of new patients and information at the receiving clinics

Notes: These figures present a binned scatter plot of the residualized outcome and residualized (log-)number of new patients. Both variables in each figure are residualized with respect to clinic and year-quarter fixed effects prior to binning. The figure then bins the clinic-level observations into 20 equal-sized bins based on residualized (log-)number of new patients. Each dot represents the mean of the outcome within a bin of the explanatory variable. The solid line shows the fitted linear relationship based on the underlying data.

given quarter:

$$share_{it} = \frac{\sum_{j=1}^{J}(prescribed_{jt} \times switch_{ijt})}{\sum_{j=1}^{J} switch_{ijt}}$$

$switch_{ijt} \in \{0, 1\}$ takes the value 1, indicating that patient j switched to clinic i at time t, and 0 otherwise.

I then estimate the following model:

$$y_{it} = \beta info_{it} + \delta X_{it} + FE_i + FE_t + \epsilon_{it}$$

The candidates for the information measure $info_{it}$ are the volume and the intensity measure, $volume_{it}$ and $share_{it}$. The parameter of interest is β, which measures the effect of exposure to information on antibiotic prescribing outcome y_{it}. To isolate this effect from the mechanical changes in overall prescribing generated by incoming patients' demand for antibiotics, I focus on the outcome only for patients who have been in the same clinic throughout the entire observational period (*"non-switchers"*). Restricting the outcome to existing patients also allows me to interpret the estimated β as the effect of information spillover to these patients. X_{it} includes a set of time-varying control variables. All regressions include year-quarter fixed effects to control for time-varying factors such as seasonality in bacterial infections, as well as clinic fixed effects to control for time-invariant unobservable characteristics of individual clinics.

For the main specifications, I use the volume of prescribed new patients as the measure of information available to clinics. I also discuss and present the results using the share and other measures in Section 4.4 and Appendix Tables D.1-D.7. The volume captures the extensive margin of information: clinics that receive more new patients with prior prescriptions observe a larger number of prescribing signals. The share, defined as the fraction of new patients who are prescribed, captures the intensity or concentration of such information, abstracting from factors such as the closing clinic's size and the receiving clinic's remaining capacity. Two clinics receiving the same number of prescribed new patients may differ substantially in the share if their total inflows differ, implying different informational environments. On the other hand, clinics with the same share may receive very different volumes of prescribing histories. Conditioning on the total number of new patients, the share therefore reflects the composition of the inflow rather than its scale.

Ideally, patients would choose clinics completely at random, so that clinics are exogenously exposed to patient-specific information, and identification of β would follow directly from this random exposure. In practice, patient choices are non-random and may depend on perceived clinic characteristics, including prescribing tendencies. For example, patients with prior prescribing histories may prefer clinics they believe to be high prescribers, and clinics that receive more such patients will mechanically exhibit higher subsequent prescribing. This selection induces an upward bias in reduced-form ordinary least squares estimates, as informational exposure is positively correlated with unobserved clinic-level prescribing propensities. Patients may also select over unobservable care quality that correlates with prescribing tendencies, generating bias in the estimate. In addition, clinics that are able to accept new patients may differ systematically from other clinics. Less congested clinics may perform more thorough diagnoses and therefore prescribe less, or alternatively may prescribe more in order to retain patients. If these clinic characteristics are correlated with patient inflows, they may bias estimates in either direction.

When patient arrival at a clinic is not random, identification is only preserved under the assumption that patients do not observe clinic-specific prescribing patterns when choosing clinics. Under this assumption, the prescribing history of arriving patients, captured by $prescribed_{jt}$, is orthogonal to unobserved clinic shocks ϵ_{it}. In this case, clinics' exposure to patient prescribing histories is as good as random, and provides valid variation for identifying β. I exploit variation in the informational content carried by arriving patients following exogenous displacements to account for the bias that arises from selection in the next section.

3.2 Constructing instrumental variable from clinic closure

To identify the causal effect of exposure to information from new patients on treatments and other health outcomes of existing patients, I employ an instrumental variable strategy to account for the potential endogeneity induced by selection based on a clinic's prescribing style. I leverage the fact that patients are randomly distributed to a new clinic after the closure of their original clinic, and that closures are mostly due to the retirement of physicians and are less likely to be correlated with unobserved local conditions in ϵ_{it}. Therefore, clinic closures and the subsequent reallocation of patients constitute an exogenous demand shock to the remaining primary care clinics.

Patients arriving from closed clinics experience varying treatment styles of their original clinics that impact their realized prescriptions. For example, patients from high-prescribing style clinics are more likely to have received antibiotic prescriptions than patients from low-prescribing clinics. Exploiting this correlation between practice style and realized prescription, I instrument for information exposure using a share-weighted mean of practice styles, where the share component is the share of patients moving from a closed clinic k to clinic i among all new intakes of clinic i in a quarter. Practice style is a measure capturing antibiotic prescribing patterns of the closed clinics. Throughout the main analysis, I define practice style as the mean of antibiotic prescribing intensity, the ratio of prescriptions to consultations, among non-switchers over all the periods a clinic is observed in the data until closure. Since non-switchers account for a large and stable proportion of a clinic's patient pool, as shown in the summary statistics Table 2.1, treatment decisions for the non-switching patient population should reflect the underlying practice styles of the primary care physicians. Apart from this static measure for prescribing style, I also conduct the same set of analyses by constructing a time-varying measure to allow for the potential evolution of prescribing styles over time. Specifically, I compute a moving average of prescribing intensity to the non-switchers within 4 quarters, and construct the instrument using the same set of incoming patient shares for the receiving clinics. The estimates in Appendix Table D.10 show that the effects are comparable in size and statistical significance to the time-invariant practice style definition.

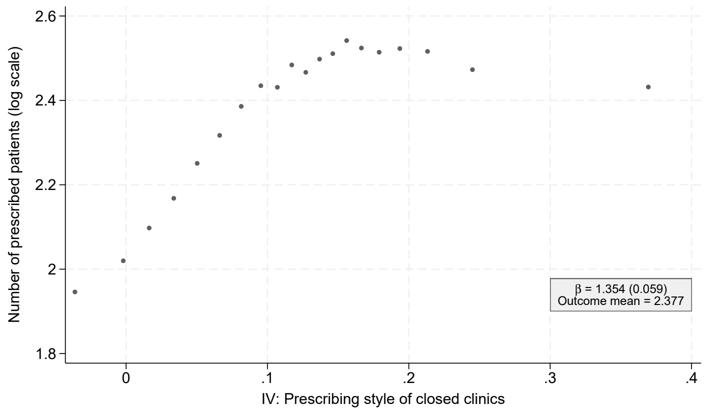


Figure 3.1: First stage regression of endogenous information measure on IV

Notes: These figures present a binned scatter plot of the residualized information measure and residualized IV. Both variables in each figure are residualized with respect to the set of controls included in the full model, and clinic and year-quarter fixed effects prior to binning. The figure then bins the clinic-level observations into 20 equal-sized bins based on residualized IV. Each dot represents the mean of the outcome within a bin of the explanatory variable. The solid line shows the fitted linear relationship based on the underlying data.

Conditional on the controls, patients' prescription histories reflect variations in the practice styles of closed clinics they experience during their time with the clinics. At the same time, clinic closures generate plausibly exogenous shifts in patients' switching decisions. The instrument thus isolates the component of information inflow composition driven by external structural shocks from closures, rather than by endogenous factors such as selective patient sorting. The instrument resembles a shift-share design:

$$z_{it} = \sum_{k=1}^{k \in G_t} s_{ikt} w_k$$

where G_t denotes the set of clinics that are closed at $t-1$. In the next period t, patients from closed clinic k come to clinic i. w_k is the practice style of these closed clinic k. s_{ikt} represents the share of patients coming to clinic i from k:

$$s_{ikt} = \frac{\sum_{j=1}^{J} switch_{ijkt}}{\sum_{k=1}^{k \in G_t} \sum_{j=1}^{J} switch_{ijkt}}$$

Therefore, z_{it} captures the share-weighted exposure of the receiving clinics to the closed clinics' practice style, driven by the redistributed patients following a clinic closure. In Figure 3.1, I show that this share-weighted practice style instrument is strongly and positively correlated with the number of previously prescribed patients arriving at the receiving clinics. Patients coming from high-prescribing style clinics are thus more likely to carry a prescribing history, and the receiving clinics, on the other hand, are more exposed to prescribing signals when they receive a higher share of patients from these clinics.

The instrument can be interpreted as valid if the correlation between origin clinic closures and prescribing outcomes at the receiving clinics operates only through the exogenous reallocation of patients from clinics with differing prescribing styles, and not through other contemporaneous shocks to the receiving clinics' own behavior. A major concern for identification is that clinic closures may not be fully exogenous to local demand conditions or to features of the primary care market that also shape prescribing behavior. For example, closures may be more likely in areas with population decline, changes in age structure, or temporary increases in infection rates. In such cases, both the inflow of patients from closing clinics and the prescribing behavior of receiving clinics may respond to the same local trends. This would bias both OLS and IV estimates. To reduce this concern, I include clinic and time fixed effects and control for observable measures of patient and physician characteristics, which absorb part of the common variation in local demand.

A related concern is that closures may reflect unobserved supply-side factors. For instance, closures may be more common among clinics that face staffing shortages, financial pressure, or stronger competition from nearby providers. Closures may also be more likely among clinics with unusually low prescribing tendencies if such clinics are less able to retain patients in competitive markets. In that case, patient reallocation after closure would reflect not only a movement of patients, but also a change in the prescribing styles present in the local market. The estimated effect of incoming patients could then partly capture how receiving clinics respond to a change in local market composition, rather than only the effect of learning from the prescribing histories of new patients. While the data do not record the reason for closure, physicians in closing clinics are on average 62 years old in my sample, which suggests that retirement is a likely explanation in many cases.

A further caveat is that closure shocks may coincide with broader structural or technological changes that also affect prescribing behavior across clinics. Closures may occur alongside regional primary care reforms or local efforts to improve antibiotic stewardship. If such changes influence both clinic survival and prescribing behavior, the instrument may partly capture these broader shocks rather than only the effect of patient inflows. In the Danish setting, however, this concern is less likely. Denmark introduced its antimicrobial resistance monitoring program in 1995, and the most recent national guideline on antibiotic prescribing was published in October 2013, several months before the start of the analysis period in 2014. This timing makes it less likely that closures after 2014 were driven by major contemporaneous policy changes in antibiotic prescribing.

To address these concerns, I perform balance tests by regressing the lagged antibiotic prescribing intensity, as well as other clinic activities, on the instrument and find no significant pre-trends in Appendix Table B.1. I also correlate clinic-level predetermined variables with the instrument and show in Appendix Table B.2 that the receiving clinics are balanced across these controls. I also test whether closures are correlated with clinic activities and characteristics that may affect prescribing styles in Appendix Figure C.2. Although physician age and the location of the clinic are relatively strong predictors of closing events, none of the other estimates are statistically significant, indicating that the closure shocks are less likely to be correlated with prescribing behaviors.

Table 4.1: Estimates of information effect on prescribing intensity

	(1) OLS	(2) OLS
Number of prescribed patients	0.0006	0.0008
	(0.0019)	(0.0018)
Clinic covariates	No	Yes
Patient covariates	No	Yes
Clinic FE	Yes	Yes
Year-quarter FE	Yes	Yes
Observations	32197	32197
Outcome mean	-2.36	-2.36
R-squared	0.77	0.77

Notes: Number of prescribed patients and outcome are in log-scale. Clinic covariates include clinic size, average physician age, share of female physicians, and share of physicians with an immigration background. Patient covariates include average patient age, share of children (age <18), share of female patients, and share of patients with an immigration background. Standard errors in parentheses are clustered at the receiving clinic level.

4 Results

4.1 Effect on prescribing intensity

Table 4.2 presents the impact of receiving previously prescribed patients on prescribing to existing patients, estimated by instrumenting the potentially endogenous patient volume with exposure to the practice styles of closed clinics. Column 1 indicates that, controlling only for clinic and time fixed effects, receiving twice as many patients with prior prescriptions increases prescribing intensity for existing patients by 2.3 percent. Controlling for clinic and patient covariates yields similar results. The increase in prescribing intensity after receiving patients with the same drug class suggests that physicians may learn from and use information generated by peer physicians and passed along by moving patients. These results also highlight an externality in the case of antibiotic prescribing, where high prescribing practice styles are transmitted through patients moving across clinics.

4.2 Effect on prescribing quality

While the baseline results show that the inflow of patients with prior prescriptions increases overall prescribing, a higher prescribing rate does not necessarily imply worse clinical practice, especially when prescriptions are indeed clinically appropriate. To better understand the nature of the adjustment in clinical practice, I evaluate prescribing quality along two complementary dimensions. First, I examine the types of antibiotics prescribed, distinguishing between broad- and narrow-spectrum antibiotics, which are commonly used indicators of prescribing quality. Second, I analyze three treatment process indicators, including diagnostic testing intensity, the frequency of prescriptions issued without prior testing, and the incidence of follow-up prescriptions. All the outcomes are again measured among clinics' existing patient pool to isolate changes in physi-

Table 4.2: Estimates of information effect on prescribing intensity

	(1) IV	(2) IV
Number of prescribed patients	0.023*	0.023*
	(0.009)	(0.009)
Clinic covariates	No	Yes
Patient covariates	No	Yes
Clinic FE	Yes	Yes
Year-quarter FE	Yes	Yes
Observations	32197	32197
Outcome mean	-2.36	-2.36
First-stage F-stat	531.01	543.18

Notes: Number of prescribed patients and outcome are in log-scale. Clinic covariates include clinic size, average physician age, share of female physicians, and share of physicians with an immigration background. Patient covariates include average patient age, share of children (age <18), share of female patients, and share of patients with an immigration background. Standard errors in parentheses are clustered at the receiving clinic level.

cians' prescribing behavior from the direct treatment needs of incoming patients. Together, these measures provide a more comprehensive view of whether the transmission of prescribing practices through patient inflows reflects changes in treatment appropriateness or simply the continuation of existing treatment patterns.

Following the classification from the Annual Epidemiological Report on Antimicrobial consumption in the EU/EEA [12], I classify antibiotic prescriptions into broad and narrow-spectrum antibiotics. A detailed list of antibiotics and their ATC codes used to construct the prescribing variables is provided in Appendix Table A.1. Narrow-spectrum antibiotics such as penicillin V, amoxicillin, and first-generation cephalosporins are primarily active against a limited range of bacteria and are typically recommended for the targeted treatment of common community-acquired infections when the likely pathogen is known. In contrast, broad-spectrum antibiotics, including macrolides, fluoroquinolones, and third-generation cephalosporins, cover a wider array of organisms and are often used empirically when diagnostic uncertainty is high. Because broad-spectrum agents exert stronger selective pressure on commensal flora and contribute more substantially to antimicrobial resistance, antibiotic stewardship initiatives promote the preferential use of narrow-spectrum options whenever clinically appropriate. Therefore, a higher proportion of narrow-spectrum prescribing is widely interpreted as an indicator of prescribing quality, reflecting accurate diagnosis, adherence to clinical guidelines, and prudent antimicrobial use.

Table 4.3 summarizes the effects of patient information on prescribing intensity of antibiotics, classified according to their spectrum of activity. Columns (1) and (3) show the IV estimates for broad and narrow-spectrum antibiotic prescribing intensity, including only clinic and time fixed effects. The estimates indicate that, when clinics receive double the number of prescribed

[12] European Centre for Disease Prevention and Control, `https://www.ecdc.europa.eu/sites/default/files/documents/ESAC-Net_report-2023.pdf`. Last accessed 09/01/2026.

Table 4.3: Estimates of information effect on prescribing intensity by antibiotic class

	Broad-spectrum		Narrow-spectrum	
	(1)	(2)	(3)	(4)
	IV	IV	IV	IV
Number of prescribed patients	0.043**	0.040*	0.022*	0.022*
	(0.015)	(0.016)	(0.011)	(0.011)
Clinic covariates	No	Yes	No	Yes
Patient covariates	No	Yes	No	Yes
Clinic FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Observations	32197	32197	32197	32197
Outcome mean	-3.93	-3.93	-2.83	-2.83
First-stage F-stat	531.01	543.18	531.01	543.18

Notes: Number of prescribed patients and outcome are in log-scale. Clinic covariates include clinic size, average physician age, share of female physicians, and share of physicians with an immigration background. Patient covariates include average patient age, share of children (age <18), share of female patients, and share of patients with an immigration background. Antibiotics are classified into broad and narrow spectrum usage at ATC level 4 or 6. Standard errors in parentheses are clustered at the receiving clinic level.

patients, the prescribing intensity of broad-spectrum antibiotics for existing patients increases by 4.3 percent, which is almost twice the effect on narrow-spectrum antibiotic prescribing (2.2 percent). Controlling for clinic and patient covariates, doubling the incoming patients with any prior prescriptions corresponds to a 4 percent increase in the broad-spectrum antibiotic prescribing intensity among non-switchers, and the effect on narrow-spectrum prescribing remains unchanged. Broad-spectrum prescribing has a substantially lower outcome mean than narrow-spectrum prescribing, yet it responds more strongly to the patient inflow shock. This finding suggests that the transmitted practice style from origin clinics is especially salient on the more discretionary margin of prescribing. I find similar prescribing patterns using the share of prescribed patients as the strength of the information signal in Appendix Table D.2, where an additional 1 percentage point (0.01) in the share increases the broad- and narrow-spectrum prescribing intensity by 1.19 percent and 0.66 percent respectively.

The increase in narrow-spectrum prescribing suggests that the spillover does not operate solely through substitution into lower-quality drugs. Rather, these estimates indicate that practice styles from origin clinics spill over into the receiving clinic's overall treatment behavior. The finding is consistent with a mechanism of information transmission: once a patient enters the receiving clinic with an antibiotic treatment history, the threshold for treatment in the same drug class for existing patients may fall because the realized treatment reduces diagnostic uncertainty. This points to a more general shift in prescribing behavior rather than quality reduction or displacement of care for the incumbent patients alone. At the same time, the stronger increase in broad-spectrum prescribing highlights the sensitivity of the lower-quality margin of antibiotic use to external information, and that the transmitted information may not necessarily be welfare-improving. In other words, patient inflows can diffuse both better and worse clinical practices. Exposure to prior treatment histories may improve treatment decisions on appropriate margins such as narrow-spectrum use, through information that may reinforce better practice styles and allow for the discovery of new treatments, but it may also propagate lower-quality prescribing styles, especially if it crowds out other treatment tools, such as diagnostic tests and guidelines.

While the increase in broad-spectrum antibiotic prescribing may signal deteriorating care quality for existing patients, it should be considered undesirable only when it results from lower diagnostic and prescribing efforts from the physicians. For example, such lower-quality prescribing may be driven by diagnostic shortcuts taken after observing information from other physicians, especially for cases where diagnostic uncertainty is high. Therefore, I also explore the effect of information exposure on three prescribing outcomes that reflect the quality of the prescribing decisions, including diagnostic testing intensity, prescriptions issued without prior testing, and the incidence of follow-up prescriptions. Diagnostic tests include all rapid tests, microscopic examinations, and bacterial cultures related to a potential bacterial infection. An antibiotic prescription is considered a prescription without prior testing if it cannot be linked to any of these tests. Specifically, if there is no test associated with a prescription 7 days prior to and after the prescribing date, it is considered a prescription without testing.[13] I consider prescriptions to have a follow-up prescription when it is followed by another antibiotic prescription of a different ATC3 subgroup within 7 days of the initial prescription. Such an adjustment of prescriptions may indicate a lower quality match of the initial prescription to the bacterial infection.

Figure 4.1 presents the estimates for the information effect on these prescribing quality indicators alongside the estimate for overall prescribing intensity from Column (2) of Table 4.2, among existing patients at the receiving clinic. The estimated coefficients are positive for all four outcomes. The effects for all prescriptions, diagnostic tests, and prescriptions before testing are similar in magnitude and are statistically significant. The coefficient for prescriptions with follow-up is also positive, although it is estimated less precisely.

The increase in overall prescribing is accompanied by an increase in diagnostic testing, indicating that clinics do not respond solely by expanding treatment while reducing clinical effort. One possible explanation is that patient inflows transmit not only prescribing outcomes as reflected by realized prescriptions, but also broader procedural practices from origin clinics. As a result, receiving clinics may change not just how much they prescribe, but also how often they use tests when treating conditions that may require antibiotics. Another possibility is that physicians differ in how they respond to the information carried by incoming patients. For physicians who remain hesitant to prescribe immediately, that information may primarily increase diagnostic testing rather than treatment itself, as prior treatment histories raise the salience of infection without fully displacing the demand for confirmation through timely testing. Under this interpretation, the informational spillover may be particularly strong on the testing margin.

[13] I allow for a 7-day delayed submission of the test to the claims database because physicians may not file all the claims on the day the treatments are carried out. In some cases, it could be delayed further. This could result in fewer untested prescriptions than the 7-day delay window.

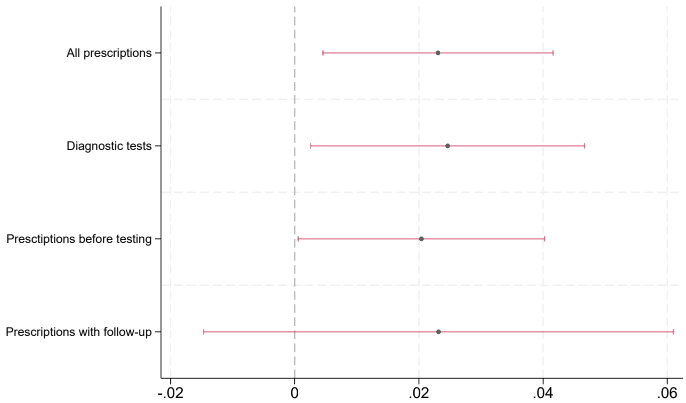


Figure 4.1: IV estimates of information effect on prescribing quality indicators

Notes: The graph plots the estimates with 95% confidence intervals from regressing antibiotic prescribing intensity and three prescribing quality indicators respectively on the log-number of incoming patients with prior antibiotic prescriptions, instrumented with an IV computed from share-weighted mean prescribing at closed origin clinics. All outcomes are measured per-consultation and in log-scale for the existing patients. All regressions include the same set of clinic and patient covariates, as well as clinic and year-quarter fixed effects, as in the main specification for prescribing intensity. Standard errors are clustered at the receiving clinic level. Complete estimation results are in Appendix Table D.16.

On the other hand, while prescriptions issued before testing also increase, prescriptions with follow-up do not rise significantly. If follow-up prescriptions are interpreted as an indicator of lower initial prescribing quality, this finding suggests that the increase in prescribing without testing does not translate into a clear increase in subsequent corrective treatment. One interpretation is that physicians become more willing to prescribe prior to testing when they can draw on information embedded in patients' prior treatment histories. In that case, information transmitted through patient inflows may partly substitute for contemporaneous testing, allowing earlier prescribing without a detectable deterioration in this downstream quality measure. Overall, the results suggest that receiving clinics respond to the information brought in by incoming patients, and that the response is reflected not only in prescribing outcomes among existing patients, but also in related treatment decisions such as diagnostic testing.

4.3 Heterogeneous response by clinic age

The baseline results identify an average learning response, but clinics may differ in how strongly they learn from the incoming information. In particular, belief updating upon the arrival of new information may vary with a clinic's years of operation, as newer clinics have less internal information to draw on, hence may be more responsive than clinics with more established practice routines. [14] To understand whether the information effect differs for newer and older clinics, I estimate an experience-specific effect by interacting the information measure with clinic age in

[14] Under a Bayesian learning framework, a clinic's years of operation may proxy for the precision of the priors because accumulated experience from observed patient outcomes can reduce uncertainty in diagnosis and treatment, thus making prior beliefs more precise as shown in Coscelli and Shum (2004). As priors become more precise, agents place less weight on new signals, implying weaker updating in response to the same information.

Table 4.4: Estimates of information effect on prescribing intensity by antibiotic class

	(1) All prescriptions	(2) Broad-spectrum	(3) Narrow-spectrum
Number of prescribed patients	0.058**	0.060	0.070**
	(0.020)	(0.032)	(0.022)
Years since entry	0.004	-0.008	0.006
	(0.004)	(0.007)	(0.005)
Number of prescribed patients $\times$Years since entry	-0.002*	-0.001	-0.002**
	(0.001)	(0.001)	(0.001)
Clinic covariates	Yes	Yes	Yes
Patient covariates	Yes	Yes	Yes
Clinic FE	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes
Observations	32197	32197	32197
Outcome mean	-2.36	-3.93	-2.83
First-stage F-stat	121.16	121.16	121.16

Notes: Number of prescribed patients and outcome are in log-scale. Clinic covariates include clinic size, average physician age, share of female physicians, and share of physicians with an immigration background. Patient covariates include average patient age, share of children (age <18), share of female patients, and share of patients with an immigration background. Antibiotics are classified into broad and narrow spectrum usage at ATC level 4 or 6. Standard errors in parentheses are clustered at the receiving clinic level.

Table 4.5: Estimates of information effect on prescribing quality indicators

	(1) All prescriptions	(2) Diagnostic tests	(3) Prescriptions before testing	(4) Prescriptions with follow-up
Number of prescribed patients	0.058**	0.051*	0.047*	0.063
	(0.020)	(0.022)	(0.021)	(0.036)
Years since entry	0.004	0.004	0.001	0.010
	(0.004)	(0.005)	(0.004)	(0.009)
Number of prescribed patients $\times$ Years since entry	-0.002*	-0.001	-0.001	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)
Clinic covariates	Yes	Yes	Yes	Yes
Patient covariates	Yes	Yes	Yes	Yes
Clinic FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Observations	32197	32197	32197	32197
Outcome mean	-2.36	-2.20	-2.72	-4.97
First-stage F-stat	121.16	121.16	121.16	121.16

Notes: Number of prescribed patients and outcome are in log-scale. Clinic covariates include clinic size, average physician age, share of female physicians, and share of physicians with an immigration background. Patient covariates include average patient age, share of children (age <18), share of female patients, and share of patients with an immigration background. Antibiotics are classified into broad and narrow spectrum usage at ATC level 4 or 6. Standard errors in parentheses are clustered at the receiving clinic level.

years, calculated as the difference between the observed year and the year when the clinic first opened, with the following model:

$$y_{it} = \beta_1 info_{it} + \beta_2 info_{it} \times age_{it} + \beta_3 age_{it} + \delta X_{it} + FE_i + FE_t + \epsilon_{it}$$

Variable age_{it} measures a clinic i's years of operation in the market until time t. To obtain a causal estimate, I also interact the instrumental variable with age_{it}.

Column (1) of Table 4.4 indicates that every additional year of experience reduces the information effect from receiving patients with prior prescriptions by 0.2 percent. According to this estimate, when presented with twice the volume of information, a newly opened clinic within a year ($age_{it} = 0$) responds by prescribing 5.8 percent more upon a consultation from existing patients, whereas a 10-year-old clinic increases its prescribing intensity by 3.8 percent, 2 percentage points lower than the new clinic. This finding implies that exposure to incoming patients from prescribing-intensive origin clinics increases antibiotic prescribing among incumbent patients, but the size of this response declines as the receiving clinic becomes more established. In other words, younger clinics are more responsive to the information carried by incoming patients, while older clinics react less strongly, consistent with predictions from Bayesian belief updating models.

Similarly, for narrow-spectrum prescribing intensity, the positive main effect combined with the negative interaction implies that the impact of incoming information is largest when clinic age is low and becomes smaller with each additional year since entry. The estimates for broad-spectrum antibiotics show similar patterns, although not statistically significant. Given that broad-spectrum prescribing is much less common, as reflected in its lower outcome mean, the estimates are also less precise. The estimates also imply that the larger average effect on broad-spectrum prescribing in the baseline results (Table 4.3) is not primarily driven by differences across clinic age. Together with the result on overall antibiotic prescribing, I find that younger clinics respond to the external information more strongly, by shifting towards a more desirable category of antibiotic use.

Other quality indicators, such as the intensity of diagnostic testing and prescriptions without testing, show a similar pattern in Table 4.5. Younger clinics increase both testing and pre-testing prescribing among existing patients when exposed to incoming information, yet the absence of a significant interaction suggests weaker evidence that this response declines systematically with clinic age. Same as the overall results from Figure 4.1, I find no statistically significant evidence of an information effect on prescriptions that require a corrective follow-up prescription.

In Appendix Table D.12 and D.13, I show that the response to information does not vary by physician age. Therefore, within-clinic information stock seems to be more relevant than physician experience. Younger clinics are more sensitive to external information because they may have less settled workflows and weaker internal norms, which allow them to react more flexibly when they receive patients from origin clinics with different prior prescribing practices. Newer clinics that have fewer listed patients may also be more likely to exert effort in adjusting their treatment behavior to retain the existing patients. Older clinics, in contrast, are more

Table 4.6: Estimates of information effect on prescribing intensity using different windows

	(1) Baseline	(2) Past 4 quarters	(3) Past 8 quarters
Number of prescribed patients	0.023*		
	(0.009)		
Patients prescribed 4 quarters before switch		0.024*	
		(0.010)	
Patients prescribed 8 quarters before switch			0.023*
			(0.009)
Clinic covariates	Yes	Yes	Yes
Patient covariates	Yes	Yes	Yes
Clinic FE	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes
Observations	32197	32197	32197
Outcome mean	-2.36	-2.36	-2.36
First-stage F-stat	530.41	514.94	537.44

Notes: Number of prescribed patients and outcome are in log-scale. Clinic covariates include clinic size, average physician age, share of female physicians, and share of physicians with an immigration background. Patient covariates include average patient age, share of children (age <18), share of female patients, and share of patients with an immigration background. Standard errors in parentheses are clustered at the receiving clinic level.

likely to have established ways of treating patients, so the same incoming information has less effect on how they treat incumbents.

4.4 Robustness

When constructing the information signal, I use all switching patients between 2014 and 2019 who have received *any* antibiotic prescriptions, assuming that physicians at the receiving clinics view historical prescriptions as a per-patient uniform signal regardless of the prescribed date or volume. In Appendix Table D.1 and D.4, I show that the estimated information effect is robust to alternative forms of this signal specification, including the share of prescribed patients and the raw number of prescribed patients instead of the log-number.

I further test the robustness of the signal specification by restricting the prescription date of the incoming patient, first because patients may be more likely to communicate recent prescriptions prior to switching, sending a stronger signal to the physicians, and physicians may interpret newer prescriptions as a signal for recent developments or trends in the local prescribing environment. To ensure that the results are not driven by historical signals that may no longer be relevant, I employ alternative windows for prescriptions at the origin clinics of the switching patients. I define antibiotic prescriptions within a year or two (4 or 8 quarters) as the information that switching patients carry to the receiving clinics. Appendix Figure C.1 presents the distributions of the number of patients using varying information windows. The estimate in column (1) of Table 4.6 indicates that doubling the number of patients who received antibiotics in the past 4 quarters drives up the prescribing intensity to existing patients by 2.4 percent, 0.1 percentage point larger than the effect of the information signal constructed using a larger window of 8 quarters, and the effect from using all historical prescriptions. Although the magnitudes of the estimated effects are quite close, the result demonstrates the importance of newer prescribing signals.

As an additional check, I estimate the information effect on prescribing intensity, accounting for the variations in per-patient prescriptions. For each receiving clinic, I define the per-patient prescribing rate among incoming patients as the average number of prescriptions they received from their old clinics. This measure allows for varying weights of patients in the information signal composition and heterogeneous signal intensities for the receiving clinics, especially in cases where clinics receive the same number of prescribed patients who bring different volumes of prior prescriptions. This rate also reflects the past demand for antibiotics among the incoming patients, as well as the "ease" of obtaining an antibiotic prescription experienced at their origin clinics, which may shape their expectations for their new clinics. Patients with varying historical prescriptions may also actively communicate their needs and expectations, constituting heterogeneous signal strengths for the receiving clinics. Appendix Table D.7 presents the results using the per-patient prescribing rate as the information signal. Demonstrating that the coefficients remain stable across these varied specifications reinforces the argument that physicians are engaged in a deliberate process of belief revision based on the informational content of their caseload, rather than reacting to unobserved clinic-level shocks or simple changes in patient flow.

I also evaluate the sensitivity of the estimates to the instrument construction. The instrument linearly combines two components: one part represents the shock component, leveraging patients' redistribution after the as-good-as-random clinic closure; the other part proxies for clinic practice styles that influence the prescribing information these redistributed patients carry. In the main analysis, I use the average prescribing intensity of the closed clinics to non-switchers to proxy for the underlying practice style. While this average measure over all observed periods of a clinic until closure does predict the actual prescriptions, as is shown by the first stage regression of the instrument, it may not reflect the potential changes in prescribing styles over time. Prescribing styles may vary when physicians join or leave the team, or when factors such as information exposure gradually shift the prescribing behavior. Therefore, practice styles during a relatively shorter window may better capture the practice styles patients experience before closure. I use a moving average of prescribing intensity within 4 quarters as an alternative to probe the robustness of the instrument. To reduce the bias from changes induced by patient movements, the prescribing intensity is again averaged over the non-switching patients. The estimated effects in Appendix Table D.10 are very similar to the estimates from the main specification. In fact, practice styles under the two definitions are distributed similarly in Appendix Figure C.2, which may be due to the relatively shorter span of the sample and the overall inertia in prescribing patterns.

4.5 Mechanism: information spillover or crowding out?

The model aims to estimate the effect of exposure to information brought by newly arrived patients. However, an overall increase in the number of listed patients may generate behavioral changes that could shift the quality of care delivered to the incumbent patients. Physicians may be under time pressure and spend less time on each patient, and hence be more likely to prescribe without testing. Appointments may become harder to obtain, limiting access to care services such as consultations for the existing patients. In Appendix Table E.2, I examine the possibility of care resource crowding out by regressing the outcomes that can proxy for care utilization of the existing patients on the number of new patients from closed clinics, and show that receiving more patients does not affect antibiotic prescribing intensity and the consultations for the existing patients. I only find a minor negative effect of -0.002 on the (log-)number of claims, indicating a 0.2 percent decrease in the number of claims filed for the incumbents when the patient intakes double.

Additionally, Appendix Table E.1 summarizes the estimates from regressing the instrument on the same set of outcomes, demonstrating that the instrument, the proxy for information exposure, only has an impact on the prescribing intensity rather than the total number of consultations or claims. These findings provide little evidence that exposure to higher-prescribing origin clinics reduces service use for incumbent patients. Instead, the results suggest that the identifying variation is linked specifically to prescribing behavior rather than to a general contraction in incumbent service provision.

Another falsification exercise lends credibility to the information mechanism. I relate the prescribing intensity of other drug classes to the instrument and the information measures for antibiotic prescribing. The two candidate drugs are statins[15] and drugs used in diabetes[16]. Statins and antidiabetic drugs are two major groups of medications used to manage cardiovascular and metabolic diseases. In primary care, they are typically used for long-term management of chronic diseases, whereas antibiotics are prescribed for short-term treatment of acute infections. Statins are prescribed to lower LDL cholesterol and reduce cardiovascular risk, often taken daily for years or lifelong as part of prevention strategies. Similarly, A10 drugs such as metformin, sulfonylureas, insulin, and newer agents like SGLT2 inhibitors or GLP-1 receptor agonists are used to control blood glucose in diabetes, requiring ongoing titration, monitoring, and adherence over long periods. Therefore, an increasing number of patients per primary care provider can reduce the quality of chronic care because chronic disease management requires time-intensive, continuous monitoring and individualized follow-up.

Appendix Table E.3 and E.4 show the results of regressing statin prescribing intensity to non-switchers on the instrument for exposure to information on antibiotics, and the two information measures. All three regressions yield null effects, supporting the hypothesis that the increase in prescribing is matched to the exposure to specific drugs, in this case, antibiotics.

Several other pieces of evidence are also consistent with Bayesian learning. In Section 4.3,

[15] Statins are a class of cholesterol-lowering drugs under ATC level 4 class C10AA, HMG CoA reductase inhibitors.

[16] ATC class A10.

I show that responses to the information signal are larger in relatively new clinics, which are likely to have less precise priors under diagnostic uncertainty. At the same time, I find no heterogeneous effects by physician age, suggesting that within-clinic prescribing norms may matter more for prescribing decisions. I further examine heterogeneity by clinic structure in Appendix Table D.14, splitting the sample by the number of physicians in a clinic, and find that the spillover to existing patients is driven by single-physician clinics. One interpretation is that in a multi-physician clinic, physicians may learn not only from their own experience but also from colleagues through discussion, observation, and shared routines. This internal information exchange can make the clinic's prior more precise, so external information brought by incoming patients receives less weight. In a single-physician clinic, this internal source of information is weaker, leading to larger updating when new information arrives. Together, these findings also highlight the importance of the internal information environment of clinics in shaping medical decision-making.

5 Conclusion

Primary care physicians routinely make treatment decisions under uncertainty, relying on prior experience and accumulated knowledge. Yet relatively little is known about how these beliefs are formed and updated in practice, or how they translate into persistent prescribing styles. In this paper, I show that medical information, in the form of antibiotic prescribing decisions made by physicians, can be transmitted to fellow physicians through patient movements and that physicians learn and update their behavior in response. Exploiting quasi-random patient redistribution following clinic closures, I find that clinics receiving twice as many new patients with prior antibiotic prescriptions increase their antibiotic prescribing intensity to the existing patients by 2.3 percent.

However, the practice styles that spread are not unambiguously welfare improving. The increase is in both broad- and narrow-spectrum antibiotic prescribing, as well as in prescribing before testing, suggesting that what diffuses is not only a specific, particularly low-quality prescribing, but a broader tendency toward more intensive antibiotic use. Meanwhile, physicians also become more likely to conduct diagnostic tests, without a corresponding increase in follow-up prescriptions to adjust the initial treatment. These results suggest that information consisting of realized outcomes can shift treatment procedures alongside prescribing decisions.

The heterogeneous responses across clinics further suggest that within-clinic information exchange can shape how physicians process and act on new information. Newer clinics and single-physician clinics are more responsive to prescribing signals, consistent with a greater reliance on external information when internal experience is limited. This pattern is in line with models of learning under uncertainty, in which agents place greater weight on outside signals when their priors are less precise. It also supports information transmission, rather than patient congestion, as a key mechanism.

These findings contribute to the literature on physician learning and practice variation by identifying a novel information channel operating through patient mobility rather than formal communication or institutional guidelines. The results suggest that physicians infer treatment norms from the prescribing histories embodied in incoming patients and incorporate this information into their own decision-making. Importantly, this learning mechanism operates even in the absence of direct interaction between physicians, highlighting the role of patients as carriers of medical information across providers.

From a policy perspective, these findings have implications for the diffusion of prescribing practices and the design of interventions aimed at improving antibiotic stewardship. Patient mobility can amplify both desirable and undesirable practices, implying that policies targeting individual physicians may have spillover effects beyond the directly treated clinics. The results also demonstrate that informal information transmission can be a powerful force shaping provider behavior, and should be taken into account when evaluating the persistence of practice variation and the effectiveness of information-based interventions in healthcare markets.

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A Antibiotic classifications

Table A.1: Classification of antibiotics

ATC4 or ATC6 class	Name
Broad-spectrum Antibiotics	
J01CR	Combinations of penicillins, including beta-lactamase inhibitors
J01DC	Second-generation cephalosporins
J01DD	Third-generation cephalosporins
J01(FA-FA01)	Macrolides except erythromycin
J01MA	Fluoroquinolones
Narrow-spectrum Antibiotics	
J01CA	Penicillins with extended spectrum
J01CE	Beta-lactamase-sensitive penicillins
J01CF	Beta-lactamase-resistant penicillins
J01DB	First-generation cephalosporins
J01FA01	Erythromycin
Other Antibiotics	
J01EA	Trimethoprim and derivatives
J01EB	Short-acting sulfonamides
J01EE	Combinations of sulfonamides and trimethoprim, including derivatives
J01XE	Nitrofuran derivatives
J01XX	Other antibacterials

B Pre-trend and balance tests

B.1 Pre-trend test for the instrument

Table B.1: Outcome: prescribing intensity

	(1) OLS	(2) OLS	(3) OLS
IV: Mean prescribing of closed clinics	0.032*		
	(0.013)		
IV, t+1		0.023	0.023
		(0.013)	(0.012)
IV, t+2			0.004
			(0.013)
Lagged clinic covariates	Yes	Yes	Yes
Lagged patient covariates	Yes	Yes	Yes
Clinic FE	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes
Observations	29112	26610	24354
Outcome mean	-2.37	-2.38	-2.38
R-squared			

Notes: Number of prescribed patients and outcome are in log-scale. Clinic covariates include clinic size, average physician age, share of female physicians, and share of physicians with an immigration background. Patient covariates include average patient age, share of children (age <18), share of female patients, and share of patients with an immigration background. Standard errors in parentheses are clustered at the receiving clinic level.

B.2 Balance test for the instrument

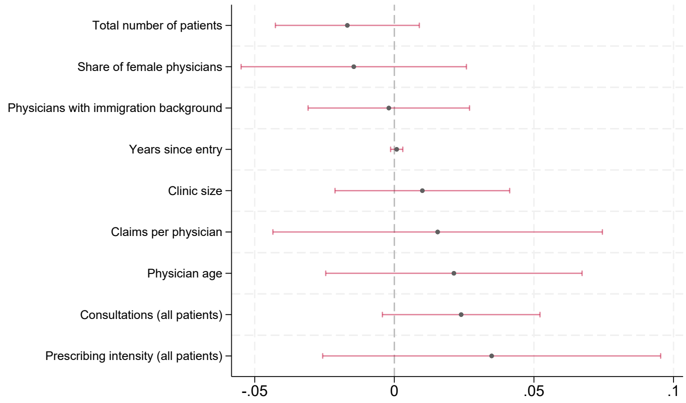


Figure B.1: Balance test for clinic activities among all patients

Notes: The graph plots the estimates with 95% confidence intervals from regressing the variables respectively on the lead instrument, controlling for time and clinic fixed effects. *Total number of patients*, *Claims per physician*, *Consultations*, *Prescribing intensity* are in log-scale. Standard errors are clustered at the receiving clinic level.

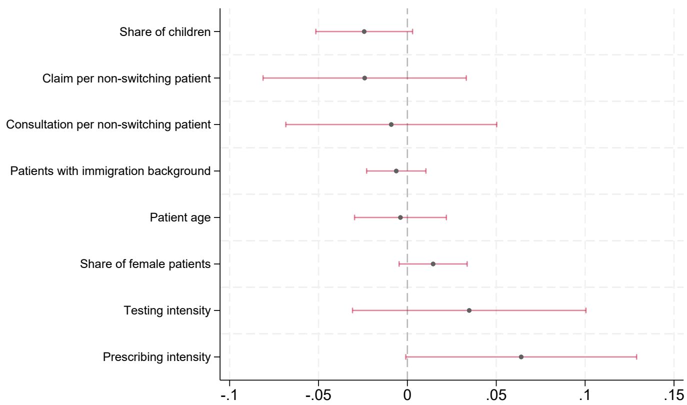


Figure B.2: Balance test for clinic activities among non-switchers

Notes: The graph plots the estimates with 95% confidence intervals from regressing the variables respectively on the lead instrument, controlling for time and clinic fixed effects. *Located in larger cities* is a 0/1 indicator for clinics located in Copenhagen, Aarhus, and Odense. *Claim per non-switching patient*, *Consultation per non-switching patient*, *Testing intensity*, and *Prescribing intensity* are in log-scale. Standard errors are clustered at the receiving clinic level.

Table B.2: Balance table for the instrument

	Coef.	Mean
Claim per non-switching patient	-.016	2.47
	(0.019)	
Claims per physician	.004	8.28
	(0.010)	
Clinic size	.013	2.23
	(0.021)	
Consultation per non-switching patient	-.002	.84
	(0.007)	
Consultations (all patients)	.015	7.82
	(0.009)	
Patient age	-.025	42.05
	(0.084)	
Patients with immigration background	-.001	.13
	(0.001)	
Physician age	.167	53.43
	(0.184)	
Physicians with immigration background	0	.08
	(0.004)	
Prescribing intensity (all patients)	.011	-2.31
	(0.009)	
Share of children	-.002	.22
	(0.001)	
Share of female patients	.001	.49
	(0.001)	
Share of female physicians	-.006	.49
	(0.008)	
Testing intensity	.016	-2.2
	(0.016)	
Total number of patients	-.01	7.89
	(0.007)	
Total quarters since entry	-.034	4.12
	(0.021)	

Notes: This table summarizes the estimates, standard error (in parentheses), and outcome mean for regressing each of the variables on the lead instrument, calculated as the mean prescribing of closed clinics. The regressions control for time and clinic fixed effects, and cluster standard error at the clinic level.

B.3 Balance test for clinic closure

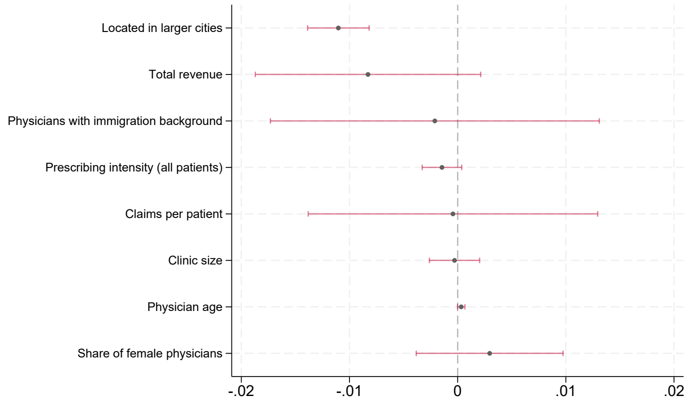
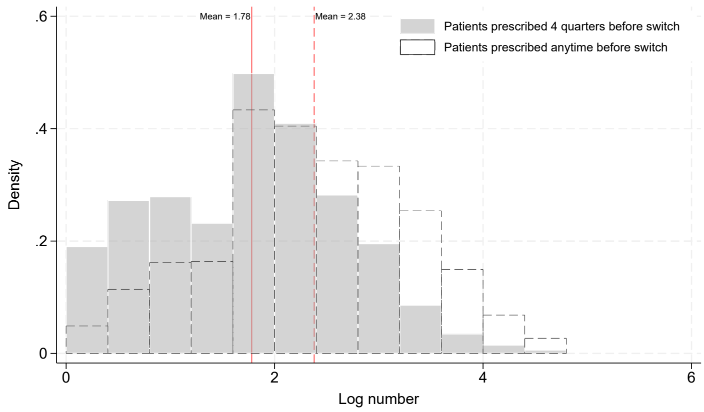


Figure B.3: Estimates of the effects of selected variables on clinic closure

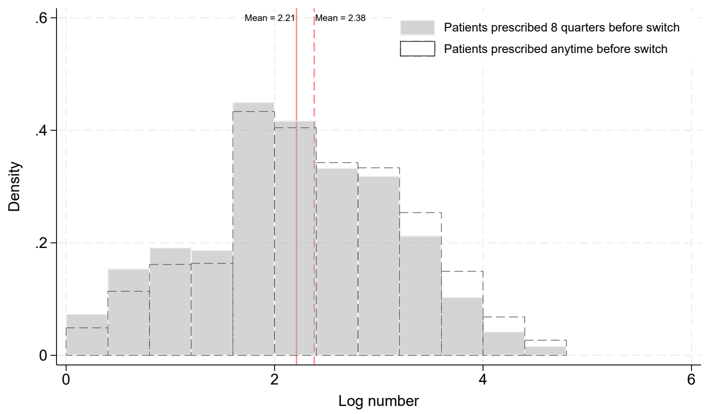
Notes: The graph plots the estimates with 95% confidence intervals from regressing a lagged 0/1 closure indicator jointly on the selected variables, controlling for time and clinic fixed effects. *Located in larger cities* is a 0/1 indicator for clinics located in Copenhagen, Aarhus, and Odense. *Prescribing intensity*, *Total revenue*, and *Claims per patient* are in log-scale. Standard errors are clustered at the receiving clinic level.

C Distribution of information measures and instruments

C.1 Distributions of patient volumes with different prescribing windows



(a) Patients prescribed within 4 quarters before switch



(b) Patients prescribed within 8 quarters before switch

Figure C.1: Distributions of incoming patients with prior prescriptions

Notes: These figures present the distributions of the information measure, defined as the number of incoming patients with prior prescribing histories of antibiotics, while restricting the prescription window to 4 and 8 quarters before switching. The number of patients prescribed anytime before switching serves as the main information measure. Number of patients is in log-scale. The log-number of patients is trimmed at 4.4 to ensure anonymity.

C.2 Distribution of the instrument using an alternative practice style definition

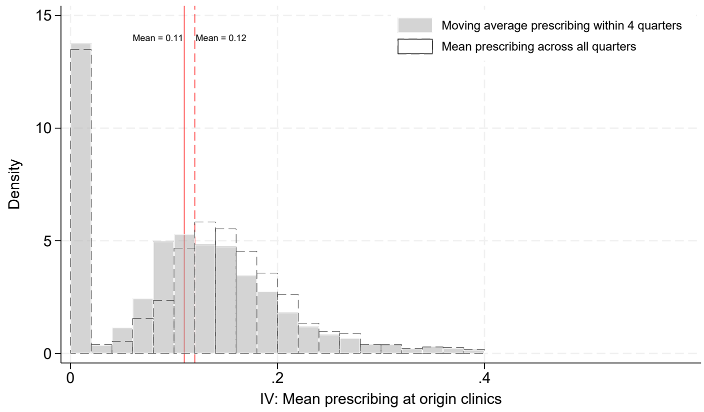


Figure C.2: Distribution of instruments

Notes: The graph plots the distributions and the mean values of the instrument constructed for the receiving clinics, using a time-invariant mean antibiotic prescribing to the non-switchers across the entire observational period as practice style, against the instrument constructed using a moving average of antibiotic prescribing intensity to the non-switchers within 4 quarters. The distribution is trimmed at an instrument value of 0.4 to ensure anonymity.

D Additional Results

D.1 Share of prescribed patients as information measure

Table D.1: Estimates of information effect on prescribing intensity

	(1) IV	(2) IV
Share of prescribed patients	0.69*	0.68*
	(0.29)	(0.29)
Clinic covariates	No	Yes
Patient covariates	No	Yes
Clinic FE	Yes	Yes
Year-quarter FE	Yes	Yes
Observations	32197	32197
Outcome mean	-2.36	-2.36
First-stage F-stat	48.60	47.95

Notes: Clinic covariates include clinic size, average physician age, share of female physicians, and share of physicians with an immigration background. Patient covariates include average patient age, share of children (age <18), share of female patients, and share of patients with an immigration background. Standard errors in parentheses are clustered at the receiving clinic level.

Table D.2: Estimates of information effect on prescribing intensity by antibiotic class

	Broad-spectrum		Narrow-spectrum	
	(1)	(2)	(3)	(4)
	IV	IV	IV	IV
Share of prescribed patients	1.28**	1.19*	0.66*	0.66*
	(0.48)	(0.49)	(0.33)	(0.33)
Clinic covariates	No	Yes	No	Yes
Patient covariates	No	Yes	No	Yes
Clinic FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Observations	32197	32197	32197	32197
Outcome mean	-3.93	-3.93	-2.83	-2.83
First-stage F-stat	48.60	47.95	48.60	47.95

Notes: Clinic covariates include clinic size, average physician age, share of female physicians, and share of physicians with an immigration background. Patient covariates include average patient age, share of children (age <18), share of female patients, and share of patients with an immigration background. Antibiotics are classified into broad and narrow spectrum usage at ATC level 4 or 6. Standard errors in parentheses are clustered at the receiving clinic level. Standard errors in parentheses are clustered at the receiving clinic level.

Table D.3: Estimates of information effect on prescribing quality indicators

	(1) All prescriptions	(2) Diagnostic tests	(3) Prescriptions before testing	(4) Prescriptions with follow-up
Share of prescribed patients	0.68*	0.73*	0.60	0.68
	(0.29)	(0.35)	(0.31)	(0.58)
Clinic covariates	Yes	Yes	Yes	Yes
Patient covariates	Yes	Yes	Yes	Yes
Clinic FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Observations	32197	32197	32197	32197
Outcome mean	-2.36	-2.20	-2.72	-4.97
First-stage F-stat	47.95	47.95	47.95	47.95

Notes: All outcomes are measured per-consultation and in log-scale. Number of prescribed patients is in log-scale. Clinic covariates include clinic size, average physician age, share of female physicians, and share of physicians with an immigration background. Patient covariates include average patient age, share of children (age <18), share of female patients, and share of patients with an immigration background. Standard errors in parentheses are clustered at the receiving clinic level.

D.2 Count of prescribed patients as information measure

Table D.4: Estimates of information effect on prescribing intensity

	(1) IV	(2) IV
Number of prescribed patients	0.0018*	0.0018*
	(0.0007)	(0.0008)
Clinic covariates	No	Yes
Patient covariates	No	Yes
Clinic FE	Yes	Yes
Year-quarter FE	Yes	Yes
Observations	32197	32197
Outcome mean	-2.36	-2.36
First-stage F-stat	115.67	120.66

Notes: Number of prescribed patients is the raw count of patients with prior prescriptions. Outcome is in log-scale. Clinic covariates include clinic size, average physician age, share of female physicians, and share of physicians with an immigration background. Patient covariates include average patient age, share of children (age <18), share of female patients, and share of patients with an immigration background. Standard errors in parentheses are clustered at the receiving clinic level.

Table D.5: Estimates of information effect on prescribing intensity by antibiotic class

	Broad-spectrum		Narrow-spectrum	
	(1)	(2)	(3)	(4)
	IV	IV	IV	IV
Number of prescribed patients	0.003**	0.003*	0.002*	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)
Clinic covariates	No	Yes	No	Yes
Patient covariates	No	Yes	No	Yes
Clinic FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Observations	32197	32197	32197	32197
Outcome mean	-3.93	-3.93	-2.83	-2.83
First-stage F-stat	115.67	120.66	115.67	120.66

Notes: Number of prescribed patients is the raw count of patients with prior prescriptions. Outcome is in log-scale. Clinic covariates include clinic size, average physician age, share of female physicians, and share of physicians with an immigration background. Patient covariates include average patient age, share of children (age <18), share of female patients, and share of patients with an immigration background. Antibiotics are classified into broad and narrow spectrum usage at ATC level 4 or 6. Standard errors in parentheses are clustered at the receiving clinic level. Standard errors in parentheses are clustered at the receiving clinic level.

Table D.6: Estimates of information effect on prescribing quality indicators

	(1) All prescriptions	(2) Diagnostic tests	(3) Prescriptions before testing	(4) Prescriptions with follow-up
Number of prescribed patients	0.002*	0.002*	0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.002)
Clinic covariates	Yes	Yes	Yes	Yes
Patient covariates	Yes	Yes	Yes	Yes
Clinic FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Observations	32197	32197	32197	32197
Outcome mean	-2.36	-2.20	-2.72	-4.97
First-stage F-stat	120.66	120.66	120.66	120.66

Notes: Number of prescribed patients is the raw count of patients with prior prescriptions. All outcomes are measured per-consultation and in log-scale. Clinic covariates include clinic size, average physician age, share of female physicians, and share of physicians with an immigration background. Patient covariates include average patient age, share of children (age <18), share of female patients, and share of patients with an immigration background. Standard errors in parentheses are clustered at the receiving clinic level.

D.3 Prescriptions per incoming patient as information measure

Table D.7: Estimates of information effect on prescribing intensity

	(1) IV	(2) IV
Prescriptions per new patient	0.17*	0.18*
	(0.07)	(0.08)
Clinic covariates	No	Yes
Patient covariates	No	Yes
Clinic FE	Yes	Yes
Year-quarter FE	Yes	Yes
Observations	32197	32197
Outcome mean	-2.36	-2.36
First-stage F-stat	48.88	46.38

Notes: Number of prescribed patients is the raw count of patients with prior prescriptions. Outcome is in log-scale. Clinic covariates include clinic size, average physician age, share of female physicians, and share of physicians with an immigration background. Patient covariates include average patient age, share of children (age <18), share of female patients, and share of patients with an immigration background. Standard errors in parentheses are clustered at the receiving clinic level.

I test the model using another definition of information that accounts for the variations in per-patient prescriptions. For each receiving clinic i, I define the per-patient prescribing rate among incoming patients as the average number of prescriptions they received from their old clinics. Formally:

$$rate_{it} = \frac{\sum_{j=1}^{J}(\#prescribed_{jt} \times switch_{ijt})}{\sum_{j=1}^{J} switch_{ijt}}$$

where $\#prescribed_{jkt}$ is the total number of prescriptions patient j at their origin clinic before switching to destination clinic i at period t.

Table D.8: Estimates of information effect on prescribing intensity by antibiotic class

	Broad-spectrum		Narrow-spectrum	
	(1)	(2)	(3)	(4)
	IV	IV	IV	IV
Prescriptions per new patient	0.32**	0.31*	0.17*	0.17*
	(0.12)	(0.13)	(0.08)	(0.09)
Clinic covariates	No	Yes	No	Yes
Patient covariates	No	Yes	No	Yes
Clinic FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Observations	32197	32197	32197	32197
Outcome mean	-3.93	-3.93	-2.83	-2.83
First-stage F-stat	48.88	46.38	48.88	46.38

Notes: Number of prescribed patients is the raw count of patients with prior prescriptions. Outcome is in log-scale. Clinic covariates include clinic size, average physician age, share of female physicians, and share of physicians with an immigration background. Patient covariates include average patient age, share of children (age <18), share of female patients, and share of patients with an immigration background. Antibiotics are classified into broad and narrow spectrum usage at ATC level 4 or 6. Standard errors in parentheses are clustered at the receiving clinic level. Standard errors in parentheses are clustered at the receiving clinic level.

Table D.9: Estimates of information effect on prescribing quality indicators

	(1) All prescriptions	(2) Diagnostic tests	(3) Prescriptions before testing	(4) Prescriptions with follow-up
Prescriptions per new patient	0.18*	0.19*	0.15	0.18
	(0.08)	(0.09)	(0.08)	(0.15)
Clinic covariates	Yes	Yes	Yes	Yes
Patient covariates	Yes	Yes	Yes	Yes
Clinic FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Observations	32197	32197	32197	32197
Outcome mean	-2.36	-2.20	-2.72	-4.97
First-stage F-stat	46.38	46.38	46.38	46.38

Notes: Number of prescribed patients is the raw count of patients with prior prescriptions. All outcomes are measured per-consultation and in log-scale. Clinic covariates include clinic size, average physician age, share of female physicians, and share of physicians with an immigration background. Patient covariates include average patient age, share of children (age <18), share of female patients, and share of patients with an immigration background. Standard errors in parentheses are clustered at the receiving clinic level.

D.4 Alternative practice style measure

Table D.10: Estimates of effects on prescribing intensity using moving average

	(1) IV	(2) IV
Number of prescribed patients	0.026**	0.026*
	(0.010)	(0.010)
Clinic covariates	No	Yes
Patient covariates	No	Yes
Clinic FE	Yes	Yes
Year-quarter FE	Yes	Yes
Observations	32197	32197
Outcome mean	-2.36	-2.36
First-stage F-stat	402.48	413.38

Notes: Number of prescribed patients and outcome are in log-scale. Clinic covariates include clinic size, average physician age, share of female physicians, and share of physicians with an immigration background. Patient covariates include average patient age, share of children (age <18), share of female patients, and share of patients with an immigration background. Standard errors in parentheses are clustered at the receiving clinic level.

D.5 Adjustments to the clinic sample

Table D.11: Estimates of information effect on prescribing intensity

	(1) Excluding takeovers	(2) Excluding new clinics
Number of prescribed patients	0.020*	0.020*
	(0.009)	(0.009)
Clinic covariates	Yes	Yes
Patient covariates	Yes	Yes
Clinic FE	Yes	Yes
Year-quarter FE	Yes	Yes
Observations	30384	28117
Outcome mean	-2.35	-2.34
First-stage F-stat	503.72	451.47

Notes: Number of prescribed patients and outcome are in log-scale. Clinic covariates include clinic size, average physician age, share of female physicians, and share of physicians with an immigration background. Patient covariates include average patient age, share of children (age <18), share of female patients, and share of patients with an immigration background. Standard errors in parentheses are clustered at the receiving clinic level.

D.6 Information interacted with physician age

Table D.12: Estimates of information effect interacted with physician age on prescribing intensity

	(1) All prescriptions	(2) Broad-spectrum	(3) Narrow-spectrum
Number of prescribed patients	0.012	0.107	0.029
	(0.063)	(0.102)	(0.075)
Physician age	0.002	0.011*	0.002
	(0.003)	(0.005)	(0.004)
Number of prescribed patients × Physician age	0.000	-0.001	-0.000
	(0.001)	(0.002)	(0.001)
Clinic covariates	Yes	Yes	Yes
Patient covariates	Yes	Yes	Yes
Clinic FE	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes
Observations	32197	32197	32197
Outcome mean	-2.36	-3.93	-2.83
First-stage F-stat	116.01	116.01	116.01

Notes: Number of prescribed patients and outcome are in log-scale. Clinic covariates include clinic size, average physician age, share of female physicians, and share of physicians with an immigration background. Patient covariates include average patient age, share of children (age <18), share of female patients, and share of patients with an immigration background. Antibiotics are classified into broad and narrow spectrum usage at ATC level 4 or 6. Standard errors in parentheses are clustered at the receiving clinic level.

Table D.13: Estimates of information effect interacted with physician age on prescribing quality indicators

	(1) All prescriptions	(2) Diagnostic tests	(3) Prescriptions before testing	(4) Prescriptions with follow-up
Number of prescribed patients	0.012	0.042	0.001	0.034
	(0.063)	(0.075)	(0.069)	(0.122)
Physician age	0.002	0.003	0.002	0.000
	(0.003)	(0.004)	(0.003)	(0.006)
Number of prescribed patients × Physician age	0.000	-0.000	0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.002)
Clinic covariates	Yes	Yes	Yes	Yes
Patient covariates	Yes	Yes	Yes	Yes
Clinic FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Observations	32197	32197	32197	32197
Outcome mean	-2.36	-2.20	-2.72	-4.97
First-stage F-stat	116.01	116.01	116.01	116.01

Notes: Number of prescribed patients and outcome are in log-scale. Clinic covariates include clinic size, average physician age, share of female physicians, and share of physicians with an immigration background. Patient covariates include average patient age, share of children (age <18), share of female patients, and share of patients with an immigration background. Antibiotics are classified into broad and narrow spectrum usage at ATC level 4 or 6. Standard errors in parentheses are clustered at the receiving clinic level.

D.7 Information effect on single-physician clinics

Table D.14: Estimates of information effect on prescribing intensity

	(1) Single-physician	(2) Multiple-physician
Number of prescribed patients	0.047**	0.003
	(0.016)	(0.010)
Clinic covariates	Yes	Yes
Patient covariates	Yes	Yes
Clinic FE	Yes	Yes
Year-quarter FE	Yes	Yes
Observations	13490	18679
Outcome mean	-2.29	-2.41
First-stage F-stat	272.93	309.18

Notes: Number of prescribed patients and outcome are in log-scale. Clinic covariates include clinic size, average physician age, share of female physicians, and share of physicians with an immigration background. Patient covariates include average patient age, share of children (age <18), share of female patients, and share of patients with an immigration background. Antibiotics are classified into broad and narrow spectrum usage at ATC level 4 or 6. Standard errors in parentheses are clustered at the receiving clinic level.

Table D.15: Estimates of information effect on prescribing quality indicators of single-physician clinics

	(1) All prescriptions	(2) Diagnostic tests	(3) Prescriptions before testing	(4) Prescriptions with follow-up
Number of prescribed patients	0.047**	0.047*	0.042*	0.032
	(0.016)	(0.020)	(0.017)	(0.032)
Clinic covariates	Yes	Yes	Yes	Yes
Patient covariates	Yes	Yes	Yes	Yes
Clinic FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Observations	13490	13490	13490	13490
Outcome mean	-2.29	-2.28	-2.62	-4.81
First-stage F-stat	272.93	272.93	272.93	272.93

Notes: Number of prescribed patients is the raw count of patients with prior prescriptions. All outcomes are measured per-consultation and in log-scale. Clinic covariates include clinic size, average physician age, share of female physicians, and share of physicians with an immigration background. Patient covariates include average patient age, share of children (age <18), share of female patients, and share of patients with an immigration background. Standard errors in parentheses are clustered at the receiving clinic level.

D.8 Companion tables to graphs

Table D.16: Estimates of information effect on prescribing quality indicators

	(1) All prescriptions	(2) Diagnostic tests	(3) Prescriptions before testing	(4) Prescriptions with follow-up
Number of prescribed patients	0.023*	0.025*	0.020*	0.023
	(0.009)	(0.011)	(0.010)	(0.019)
Patient age	0.006	0.011**	0.003	-0.036***
	(0.003)	(0.004)	(0.004)	(0.005)
Share of children	0.207	0.181	0.159	-2.665***
	(0.239)	(0.298)	(0.262)	(0.350)
Share of female patients	0.523	0.884*	0.169	-0.816*
	(0.274)	(0.343)	(0.305)	(0.407)
Patients with immigration background	-0.027	0.114	0.002	-0.671*
	(0.221)	(0.263)	(0.244)	(0.298)
Physician age	0.002*	0.002*	0.003**	-0.000
	(0.001)	(0.001)	(0.001)	(0.002)
Share of female physicians	-0.026	0.049	-0.050	-0.033
	(0.022)	(0.032)	(0.027)	(0.038)
Clinic size	-0.007	-0.021**	-0.004	-0.018
	(0.006)	(0.008)	(0.007)	(0.011)
Physicians with immigration background	0.013	-0.018	0.019	0.018
	(0.036)	(0.040)	(0.039)	(0.068)
Clinic FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Observations	32197	32197	32197	32197
Outcome mean	-2.3597715	-2.2037591	-2.7227788	-4.9653934
First-stage F-stat	543.182	543.182	543.182	543.182

Notes: All outcomes are measured per-consultation and in log-scale. Number of prescribed patients is in log-scale. Clinic covariates include clinic size, average physician age, share of female physicians, and share of physicians with an immigration background. Patient covariates include average patient age, share of children (age <18), share of female patients, and share of patients with an immigration background. Standard errors in parentheses are clustered at the receiving clinic level.

E Tests for crowding out

E.1 Care utilization outcomes

Table E.1: Reduced form OLS estimates of effects of the IV

	(1) Prescribing intensity	(2) Consultations	(3) Claims
Mean prescribing at origin clinic	0.032*	-0.012	-0.009
	(0.013)	(0.008)	(0.008)
Lagged clinic covariates	Yes	Yes	Yes
Lagged patient covariates	Yes	Yes	Yes
Clinic FE	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes
Observations	29112	29112	29112
Outcome mean	-2.37	7.09	8.17
R-squared	0.78	0.99	0.99

Notes: All outcomes are in log-scale and measured for the existing patients (non-switchers). Clinic covariates include clinic size, average physician age, share of female physicians, and share of physicians with an immigration background. Patient covariates include average patient age, share of children (age <18), share of female patients, and share of patients with an immigration background. Standard errors in parentheses are clustered at the receiving clinic level.

Table E.2: Reduced form OLS estimates of effects of the number of patients from closed clinics

	(1) Prescribing intensity	(2) Consultations	(3) Claims
Number of new patients	0.001	-0.002	-0.002*
	(0.001)	(0.001)	(0.001)
Lagged clinic covariates	Yes	Yes	Yes
Lagged patient covariates	Yes	Yes	Yes
Clinic FE	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes
Observations	29112	29112	29112
Outcome mean	-2.37	7.09	8.17
R-squared	0.78	0.99	0.99

Notes: All outcomes are in log-scale and measured for the existing patients (non-switchers). Number of new patients is in log-scale and refers to the number of patients coming from a closed clinic. Clinic covariates include clinic size, average physician age, share of female physicians, and share of physicians with an immigration background. Patient covariates include average patient age, share of children (age <18), share of female patients, and share of patients with an immigration background. Standard errors in parentheses are clustered at the receiving clinic level.

E.2 Placebo outcomes

Table E.3: Estimates of effects on prescribing intensity of statin

	(1) OLS	(2) IV
IV: Mean prescribing of closed clinics	0.010	
	(0.014)	
Number of prescribed patients (antibiotics)		0.008
		(0.010)
Clinic covariates	Yes	Yes
Patient covariates	Yes	Yes
Clinic FE	Yes	Yes
Year-quarter FE	Yes	Yes
Observations	31924	31924
Outcome mean	-2.28	-2.28
First-stage F-stat		538.45

Notes: Number of prescribed patients and outcome are in log-scale. Clinic covariates include clinic size, average physician age, share of female physicians, and share of physicians with an immigration background. Patient covariates include average patient age, share of children (age <18), share of female patients, and share of patients with an immigration background. Standard errors in parentheses are clustered at the receiving clinic level.

Table E.4: Estimates of effects on prescribing intensity of antidiabetic drugs (A10)

	(1) OLS	(2) IV
IV: Mean prescribing of closed clinics	-0.008	
	(0.035)	
Number of prescribed patients (antibiotics)		-0.006
		(0.026)
Clinic covariates	Yes	Yes
Patient covariates	Yes	Yes
Clinic FE	Yes	Yes
Year-quarter FE	Yes	Yes
Observations	32197	32197
Outcome mean	-2.28	-2.28
First-stage F-stat		543.18

Notes: Number of prescribed patients and outcome are in log-scale. Clinic covariates include clinic size, average physician age, share of female physicians, and share of physicians with an immigration background. Patient covariates include average patient age, share of children (age <18), share of female patients, and share of patients with an immigration background. Standard errors in parentheses are clustered at the receiving clinic level.